

Examining Gang Social Network Structure And Criminal Behavior

by

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ABSTRACT

The current study examines the social structure of local street gangs in Glendale, Arizona. Literature on gang organization has come to different conclusions about gang organization, largely based on the methodology used. One consistent finding from qualitative gang research has been that understanding the social connections between gang members is important for understanding how gangs are organized. The current study examines gang social structure by recreating gang social networks using official police data. Data on documented gang members, arrest records, and field interview cards from a 5-year period from 2006 to 2010 were used. Yearly social networks were constructed going two steps out from documented gang members. The findings indicated that gang networks had high turnover and they consisted of small subgroups. Further, the position of the gang member or associate was a significant predictor of arrest, specifically for those who had high betweenness centrality. At the group level, density and measures of centralization were not predictive of group-level behavior; hybrid groups were more likely to be involved in criminal behavior, however. The implications of these findings for both theory and policy are discussed.

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TABLE OF CONTENTS

	Page
LIST OF TABLES	vi
LIST OF FIGURES	vii
CHAPTER 1: INTRODUCTION	1
CHAPTER 2: REVIEW OF THE LITERATURE	7
Gang organization: How we know what we know	7
Self-report gang research and gang organization.	13
Social Cohesion and Social Learning Theories	25
Social Networks and Gangs	33
Current Study	41
Research Questions	43
CHAPTER 3: METHODOLOGY	45
Setting.....	45
Data collection.....	52
CHAPTER 4: CREATING NETWORKS FROM OFFICIAL POLICE DATA	62
Analytic Strategy	62
Findings	64
Summary of Findings	81
CHAPTER 5: NETWORK POSITION AND CRIMINAL BEHAVIOR.....	84
Analytic Strategy	84
Findings	87
Summary of findings.....	91

	Page
CHAPTER 6: GANG SOCIAL STRUCTURE.....	95
Analytic Strategy	95
Findings	100
Summary of Findings	112
CHAPTER 7: DISCUSSION AND CONCLUSIONS	116
Limitations	117
Major Findings and Implications	120
Future Research	138
REFERENCES	141
APPENDIX A.....	153
APPENDIX B	156

LIST OF TABLES

	Page
Table 3.1: 2010 U.S. Census estimates.....	46
Table 3.2: Crimes reported to law enforcement from 2006-2010	49
Table 4.1: Individual descriptives by year	67
Table 4.2: Network descriptives by year	71
Table 4.13: All possible yearly combinations fo being in the network	80
Table 5.1: Logistic regression, effect of centrality on being arrested.....	93
Table 5.2: Logistic regression, effect of interaction of centrality and gang membership on being arrested	94
Table 6.1: Level of transitivity by year using Zero-One	102
Table 6.2: Average levels of density and centralization	106
Table 6.3: Regression of arrest on group-level control variables	111
Table 6.4: Regression of arrest on group-level variables	112

LIST OF FIGURES

	Page
Figure 3.3: Violent crime rate by year	50
Figure 3.4: Property crime rate by year	50
Figure 4.3: Social network in 2006.....	72
Figure 4.4: Social network in 2007.....	73
Figure 4.5: Social network in 2008.....	73
Figure 4.6: Social network in 2009.....	74
Figure 4.7: Social network in 2009.....	74
Figure 4.8: 2006 network with clique affiliations.....	76
Figure 4.9: 2007 network with clique affiliations.....	76
Figure 4.10: 2008 network with clique affiliations.....	77
Figure 4.11: 2009 network with clique affiliations.....	77
Figure 4.12: 2010 network with clique affiliations.....	78

CHAPTER 1: INTRODUCTION

The structure of a group is related to its function. Structure determines how well group members perform their function and how that function evolves. Given the relationship between structure and function, a critical understanding of a group's structure presents opportunities to intervene in its functional outcomes. Not all groups are socially significant, but some are. In certain cases, then, society has an interest both in the function of a group and in the group's level of success in carrying out its function. This is true both for pro-social and antisocial groups. In particular, society is deeply involved in the effort to alter the functional outcomes of groups involved in crime. Among groups with criminal functions, social scientists in the U.S. have been focusing on one in particular group -- the street gang -- for more than a century, in part, because of its widespread social and economic impact on communities. Much of that research has focused on understanding gang structure as a means of understanding how gangs function, hoping that will lead to effective interventions for social service, law enforcement, and other criminal justice agencies. The current research is motivated by the potential to advance our understanding not of gangs' formal structures, which have been researched at length, but of something more complicated, fluid, and "real," their complex on-the-street operating networks. To this end, the current study taps into a rich, but comparatively unused, data source; testing and assuring the usefulness of that data, and exploring analytic approaches to use it for the purpose of unlocking the informal social structures of gang members.

Data from the National Gang Center's National Youth Gang Survey indicate that gangs are a pervasive problem in the United States. In 2009, about 34.5% of U.S. jurisdictions reported having a gang problem (Egley & Howell, 2011). The data indicated that there were more than 28,000 gangs and about 731,000 gang members in 3,500 jurisdictions in 2009. Gangs and gang members are disproportionately involved in violence. From 2002 to 2006, about 7,800 gang-related homicides were committed across the largest 100 cities in the United States (Decker & Pyrooz, 2010); they accounted for nearly 25% of all homicides among those cities.

Researchers have determined that gang members are more likely to be involved in criminal behavior as a result of their participation in the gang (Thornberry, Krohn, Lizotte, & Chard-Wierschem (1993). One explanation proposed for this increase in delinquent and criminal behavior is that increases in gang organizational structure facilitate increases in criminal behavior (Jankowski, 1991; Taylor, 1990; Decker, Katz, & Webb, 2008). The problem is that researchers have largely assumed that group structure is related to behavior, but rather than this connection having been quantitatively or qualitatively shown, it has only been implied. Additionally, researchers have relied on observational studies and dichotomous indicators of gang organization to relate gang form to function. Therefore, while some evidence has shown an association between gang structure and behavior, gang researchers have struggled to clearly identify which specific characteristics of gangs are significantly related to behavior. Moreover, gang research has been hindered by the inability to collect data at the group level (Short, 1998), which has made examining the relationship between structure and behavior that much more difficult.

The existing gang literature is limited with respect to the study of gang organization. First, the literature has been limited by the sparse availability of group-level data (Klein, 2005). Qualitative research has provided valuable information about the important roles of structure and organization; these studies have not been generalizable, however. Self-report studies, on the other hand, suggest that gang organization is related to criminal behavior.

One of the limitations of self-report studies is their reliance on individual perceptions of group organization (Decker et al., 2008). Second, researchers of gang organization have not identified which characteristics of gangs are related to criminal behavior. More research is needed on gangs at the group level, and more information is needed about how and why group structure is related to behavior.

To build on prior gang literature, the current study will use a social network perspective to examine gang organization. Group dynamics and organizational structure have long been important concepts in gang research (Cohen, 1955; Short & Strodtbeck, 1965); however, gang research using social network methodologies has lagged behind. Social network analysis has much to offer the body of literature on gang organizational structure. Specifically, the network approach can help quantify how social structures matter at the group level and how certain positions in a web of social relationships might be more important than other positions in terms of criminal behavior.

In order to expand on the current gang literature, the current study will examine three research questions. First, can relational data gathered from the police be used to examine social networks? It is important to know whether this methodological approach

is viable for the study of gangs. Official police data are ubiquitous, and using these data in new ways would open up new opportunities for research and policy.

Second, are individuals most central to a social network those who are most criminally active and, related, what network positions are most associated with criminal involvement? Not only is group structure important, but since crime is committed by individuals, it is important to know which position in the group is likely to be the most criminal. Social learning theory would suggest that those who are most central in a deviant group will be most criminal.

Third, what are the network structures that differentiate gangs, and which are related to group-level criminal behavior? One of the major gaps in the literature has been the availability of group-level data. This study examines such data. Further, the social cohesion of groups is important. The current study is able to measure the social structure of gangs and assess the levels of social cohesion that are present.

Theoretically, this study will examine the premise that social cohesion and social influence are mechanisms through which social networks affect behavior. For a number of reasons, the current study is important for theory development. First, little is known about the group structure of gangs. Having more information about the social structure of gangs and the positions within them will allow researchers to refine their understanding of the mechanisms through which gangs facilitate the criminal behavior of their members. Second, a better understanding of gang structure will allow researchers to assess the applicability of criminological theories for gang and non-gang groups. If increases in social cohesion in gangs lead to more criminal behavior, what do similar increases in social cohesion lead to in non-delinquent youth groups?

In terms of policy, knowing how different gang structures and positions are related to criminal behavior might have an impact on how gangs should be addressed by law enforcement and social services. Law enforcement strategies and social services might be organizationally and operationally designed based on the social structure of the targeted gang. Similarly, suppression, intervention, and prevention efforts might be tailored to individuals based on their position in the gang.

Before answering the research questions, I will provide an assessment of the literature in the next chapter, proceeding in three stages. First, the literature on gang organizational structure and the methodologies that have been used to measure gang organization will be examined. This review will include previous studies that have attempted to analyze the organizational structure of gangs and how the organizational structure relates to gang behavior, highlighting those studies' strengths and limitations. This chapter will also discuss the types of gang data that have been used to construct our understanding of gang organization, and how this data has influenced our understanding of the issues.

Following this discussion, I will propose two theoretical frameworks for understanding gang organizational structure through social networks: social cohesion and social learning. Social cohesion sheds light on the meaning of group-level structures, while social learning helps us understand the importance of social position in the gang.

Finally, the literature on gangs, criminology, and social networks will be reviewed. In this section, I will consider the meaning of network structures for gangs and review the gang research that has incorporated social network analysis. Additionally, this section will outline the methodological and theoretical strengths of social network

analysis. I will discuss the ways in which social network analysis has been used in criminology and how it provides an important conceptual and methodological framework for understanding gang organizational structure.

Following the assessment of the literature, I will present the research questions for the current study. The third chapter will outline the data collection methodology and outline the analytic strategy of the present study. I will introduce three sources of data, which were collected and merged to create an analyzable relational data set, and describe the process of creating a social network that expands two steps out from current gang members.

CHAPTER 2: REVIEW OF THE LITERATURE

Gang organization: How we know what we know

Gang organization has been conceptualized in different ways, and the literature on gang organization has not always been consistent with respect to findings. The literature has developed around three distinct methodologies: (a) ethnographic/qualitative data; (b) self-reported survey data; and (c) official law enforcement data. General conclusions about gang organization have been associated with each of these methodologies.

For early gang researchers, ethnographies were the method of choice. The best known of these was written by Frederic Thrasher in the early 20th century. In the 1960s, self-report methods gained popularity in the social sciences bringing new insights to our understanding of gang organization. Eventually, law enforcement data were incorporated through secondary data analysis and surveys of law enforcement agencies.

Each type of data has come with its own limitations and advantages. As the literature on gang organization has developed and evolved, the conclusions presented generally have been related to the researcher's choices of methodology.

Qualitative gang research and gang organization.

Gangs were a focus of many early criminological studies (Thrasher, 1927; Puffer, 1912; Lewis, 1912), and gang ethnographies have spanned the life of gang research (for example, Thrasher; Miller, W., 1958; Short & Strodtbeck, 1965; Yablonsky, 1962; Klein, 1971; Hagedorn, 1998; Miller, J., 2001). Although early studies were confined to major U.S. cities, more recently ethnographies have been conducted in European countries, as well. (See Decker & Pyrooz, 2012, for a review).

Ethnographies have provided a tremendous amount of in-depth information on specific gangs, which is fortunate because, as Frederic Thrasher (1927) noted early on, no two gangs are alike. Gang ethnographies offer rich, detailed information about gang organization and social processes. Thrasher's classic work on gangs in Chicago produced findings that still are relevant today. He collected data from 1,313 Chicago gangs using a variety of qualitative methods. His work made it clear that each gang is unique, depending on the strength of the organization or leadership, and often depending on the personalities of those involved. Thrasher emphasized that the social structure of gangs was made up of "intimacies," small groups of two or three boys; it was in these small groups that activities were carried out. He also emphasized the importance of interpersonal relationships in gang organization. To this day, we know little about the importance of the gang's social structure.

Thrasher (1927) further identified different types of gangs and the ways in which they evolved, if conditions were right, from an unorganized and loosely knit group to an organized gang. He posited that gangs became more organized in the presence of external conflict and the absence of internal problems. As gang members aged and matured, gangs could evolve in a number of different ways. If a gang became involved in pro-social community activities, it might become a "conventionalized" gang, a social club of sorts for dancing or billiards. If the gang did not become involved in community activities, it would not become integrated into the community and it could evolve instead into a criminal gang. Thrasher's work suggests that groups evolve and their organizational structures and purposes change over time.

An important early work of gang research by Whyte (1942) also highlighted the importance of relationships. In a 3½-year participant observation study in Boston, the author found that there were different social positions in each group. Even as a group's membership turned over, the group's social structure would persist. At the bottom were the corner boys, then the intermediaries, followed by the college boys at the top. Corner boys would not interact with college boys because of the social distance between the two groups. Relations were the fabric of the social organization of the corner boys. Corner boys' social interests revolved around the community, while the college boys were focused primarily on social mobility. Whyte was one of the early researchers to identify age-graded subgroups.

Additional work (still being organized and understood) was conducted by Walter Miller in Boston the mid-1950s. His book, *City Gangs*, was recently published in full form (Decker, 2012). Miller's work, along with giving us other insights, highlights the importance of relationships and social networks to gangs. Miller used no formal social network analysis techniques, but clearly he understood the importance of social networks and their influence on behaviors. Specifically, he noted that gangs had built such a strong "interdependency that group members were reluctant to engage in many kinds of behavior unless they were accompanied by other group members" (Decker, p. 514). The large number of contact cards Miller had collected underscored his recognition that relational systems were important. Each card detailed information about individuals or about those with whom they came in contact (Decker).

Since the 1980s, the gang literature resulting from qualitative research has generally presented two perspectives on gang organization, one being that they are

formal-rational organizations (Skolnick, 1990; Sanchez-Jankowski, 1991; Venkatesh, 1997), the other being that they are loose-knit groups (Hagedorn, 1998; Decker & Van Winkle, 1994; Fleisher, 1995). Early studies focused on exceptional gangs in major cities; thus, researchers were led to believe that most gangs were well-organized. As more research was conducted in other cities around the country, it became evident that gangs were generally not as organized as some believed (Decker & Van Winkle). Research reporting that gangs were formal-rational organizations asserted that gangs had leadership structures, rules for members to follow, and an ability to at least somewhat control the behavior of their members.

Skolnick, Correl, Navarro, & Rabb (1990) conducted 80 qualitative interviews with 39 inmates incarcerated at California correctional institutes and 42 law enforcement and corrections officers. They found that while gangs in northern California were organized around drug distribution, gangs in southern California were organized around neighborhood and culture. Even though the cultural gangs were not formed for the explicit purpose of drug sales, Skolnick et al. found that the organizational structure of the cultural gangs facilitated drug distribution in their territories.

Similarly, Sanchez-Jankowski (1991) depicted gangs as organized groups with leadership structures, codes of conduct, and collective goals. Based on his work over 10 years among 37 gangs in three cities, Sanchez-Jankowski concluded that gangs organized in order to increase profits for the purposes of the betterment of the gang. His findings clearly depicted gangs as formal-rational organizations whose structures enabled increasing criminal behavior. According to Sanchez-Jankowski, “gangs with very limited structures are in a state of withering away” (p. 99).

Additional research in Detroit (Mieczkowski, 1986; Taylor, 1990) supported the finding that gangs were well-organized and that their organization was related to their criminal behavior (i.e., drug dealing). In Detroit, Mieczkowski conducted interviews with 14 heroin dealers. The author found that drug distribution networks were highly organized and capable of being adapted to their environment. Specifically, leaders of the organization actively recruited minors to run drugs. They rationalized that minors could be paid less and would not be punished as harshly as adults by the judicial system. The gang was organized around drug distribution and its organization supported this activity.

Taylor (1990) identified three types of gangs in Detroit: (a) scavenger, (b) territorial, and (c) corporate gangs. Scavenger gangs were characterized by a lack of consistent leadership and planning of group activities. Territorial gangs emerged, according to Taylor, when a scavenger gang decided that something or someone belonged to its gang; the territorial gangs were somewhat more organized and had more consistent leadership. Corporate gangs were the most organized; they were dedicated to drug distribution. Taylor described this as a three-stage evolution of gangs becoming more organized. He found that individual gangs would evolve from being neighborhood scavenger or territorial groups into organized corporate gangs which were more efficient drug-distribution organizations.

Based on a 4-year participant observation study, Venkatesh (1997) found that a gang in Chicago did not just focus on monetary gain. Instead, the author found, gang members were a social force in the community, developing relationships with community leaders and participating in community activities. Venkatesh portrays the street gang as a highly organized group that tried to become a “more legitimate social actor in the

community” (p. 108). Unfortunately, it is difficult to generalize these findings to a broader understanding of gang organization.

This body of prior qualitative research suggests that the factors indicative of an organized gang are (a) evidence of a leader or a leadership hierarchy; (b) rules that members have to follow; (c) collective use of money for the purpose of the gang; and (d) common goals held by members. The assumption is that with more structure, the gang becomes more efficient at what it does. Thus, the more structured gangs become, the more criminally involved they should become. Researchers have assumed, for example, that as a gang becomes more organized, it becomes more effective at distributing drugs. Hagedorn (1994) challenged the proposition that more organized gangs are more efficient. Specifically, he suggested that loosely organized gangs would be better able to withstand unstable criminal and drug market environments.

Researchers debate the extent to which gangs are organized, and they also debate the impact of gang organization on member involvement in crime. In the late 1990s, there was a shift in the general conclusions about the extent to which gangs were organized. Additional research was finding that gangs were not organized, but instead were loosely knit informal groups. Multiple authors have come to this conclusion in cities across the United States including San Diego (Sanders, 1994); St. Louis (Decker & Van Winkle, 1994; Decker, Bynum, & Weisel, 1998); Milwaukee (Hagedorn, 1998); Denver, Cleveland, and Columbus (Huff, 1996); Seattle (Fleisher, 1995); San Francisco (Waldorf, 1993); and Los Angeles (Klein, Maxson, & Cunningham, 1991). The above authors concluded that there is little evidence that gangs are organized crime groups; rather, they

commonly lack an effective organizational structure, and rarely do their members share and collectively strive toward common goals.

For example, Decker & Curry (2002) found gangs to be loosely organized informal-diffuse groups. Their data indicated that gangs were aggregates of individuals with their own motivations for selling drugs. Decker et al. (1998) examined notoriously well-organized gangs in Chicago and San Diego and found that only one (Gangster Disciples) matched the definition of an instrumental-rational gang, becoming increasingly organized in order to sell drugs more efficiently. Thus, the bulk of the evidence seemed to support the view that gang members acted more as individuals than as parts of a well-organized group (Hagedorn, 1994; Decker et al.).

Note that the debate over gang organization outlined above was based on qualitative methodologies. As researchers began to rely on survey-based research, their conclusions about gang organization and the relations between gang organization and crime evolved as well. No longer was the debate between the dichotomous conclusions of instrumental or diffuse gangs. Instead, researchers started to quantitatively define gang organizational structure.

Self-report gang research and gang organization.

Survey researchers have largely studied gang organization using a criteria-based method. With self-report methods, researchers have been able to obtain larger, more representative samples, although with less detail and specificity. Prior research using self-report methodologies has relied on asking gang members to check the boxes of gang attributes that best represent the organizational features of their gangs (see, for example, Decker et al., 2008). The findings based on this method have suggested that the gangs

studied were generally not well-organized, and that their organizational structures existed on a continuum.

Studies relying on self-report survey data obtained from gang members have undoubtedly added to our knowledge. Standardized surveys have allowed researchers to compare membership prevalence, youth experiences, and risk factors of gang membership. Studies such as the Denver Youth Survey, Pittsburgh Youth Study, Rochester Youth Development Survey, and Gang Resistance Education and Training (Esbensen & Osgood, 1997; Esbensen, Winfree, Hi, & Taylor, 2001) have contributed greatly to our understanding of gangs and gang members. Self-report data is comparatively easy to collect and they offer vast amounts of information, but the methodology does not permit the same depth or group-level understanding of gang organization as qualitative research.

The advantage of survey research is that it enables greater sample size, increased generalizability, and more variation. As a result, this approach has allowed researchers to further examine the relation between gang organization and delinquent and criminal behavior in numerous contexts.

Recent qualitative gang research has argued that gangs are generally unorganized and are not formal-rational organizations, and that there is variation in gang organization. For these reasons, recent survey research has attempted to gauge levels of gang organization using a scale variable, with “disorganized” being at one end of the continuum and “highly organized” on the other end. Researchers have examined the association between gang organizational structure and criminal behavior using self-report surveys of gang members. That is, the researchers have shown that form is related to

function. Klein & Maxson (2006) pointed out that “to ignore structural differences also yields misunderstanding of functional differences” (p. 165).

By placing organization on a scale, researchers have been able to identify how a gang’s level of organization affects levels of delinquency and victimization. There are six survey-based studies that have examined this (Decker et al., 2008; Sheley, Zhang, Brody, & Bright, 1995; Bouchard & Spindler, 2010; Pyrooz, Fox, Katz, & Decker, 2011; Esbensen et al., 2001; Bjerregaard, 2002).¹ Together, these studies suggested that gangs are fairly unorganized, but also that increases in organization are related to increased delinquency and victimization.

Two studies have indirectly shown that organization is related to the type of behavior that members engage in (Esbensen et al., 2001; Bjerregaard, 2002). Esbensen et al. categorized youth based on an increasingly restrictive definition of their involvement in a gang. One of the criteria was the gang’s level of organization, measured by whether the gang had a leader, special symbols and colors, and initiation procedures. Similarly, Bjerregaard used an increasingly restrictive definition of a group’s organization to determine whether increased self-reported group structure was related to increases in theft, criminal justice involvement, and firearm involvement. Important to the current discussion, the authors found that individuals who were members of more structured groups tended to have more favorable attitudes toward firearms and were involved in more delinquency. Both of these studies pointed toward the finding that group structure

¹ The most direct tests of this relationship came from Decker et al. (2008), Sheley et al. (1995), Pyrooz et al. (2012), and Bouchard & Spindler (2010), while this relation was indirectly tested by Esbensen et al. (2001) and Bjerregaard (2002).

was related to delinquency. They provided evidence that something about how gangs and groups of delinquents are organized influences the behavior of those in the group.

Four other studies examined the relationship between gang organizational structure and delinquency and victimization more explicitly (Decker et al., 2008; Bouchard & Spindler, 2010; Sheley et al., 1995; Pyrooz et al., 2011). These studies also indicated that gang organization was related to offending behavior, but they raised questions about how researchers were measuring gang organizational structure and about the causal relations between structure and delinquency or crime. Sheley et al. examined incarcerated youth in four states using a dichotomous measure of organizational structure. Self-reported gang members indicating that their gang possessed three or more organizational characteristics were coded as being in a structured gang. The organizational characteristics were whether their gang had a name, leadership, regular meetings, special clothing, and a turf that they defended. The authors concluded that the gang members in “structured” gangs were more likely to engage in a number of delinquent activities (Sheley et al.).

Decker et al. (2008) came to a similar conclusion with a slightly different conceptualization of gang organizational structure. Instead of distinguishing between gangs dichotomously (i.e., structured and unstructured), the authors created a summated scale from seven indicators of organizational structure. In their study, 241 juvenile gang members recently arrested in Arizona were asked whether their gang had a leader, regular meetings, rules, punishments for breaking those rules, unique colors, signs or symbols, member roles, and money shared among members. The summated scale of these indicators was correlated with measures of violent victimization, violent offending, and

drug selling. The authors concluded that “the more organized the gang, even at low levels of organization, the more likely it was that members were involved in violent offenses, drug sales, and violent victimizations” (p.169).

A third and similar study examined the relationship between gang organization and delinquency in Canada (Bouchard & Spindler, 2010). Similar to Decker et al. (2008), the authors measured organization by summing nine items to create a scale. The study of 523 delinquent youth found that organization was related to drug sales and violent offending, but not to property offending.

Finally, recent research by Pyrooz et al. (2011), using comparative gang data from different populations (school and arrestee) and different countries (United States and Trinidad and Tobago), found that there did not seem to be an underlying factor driving the level of gang organization. The different gang organization criteria were largely unrelated to each other. Most of the indicators of gang organization were positively related to delinquency and victimization, but not one was consistent across data sets. That is, not one organizational characteristic across the data sources consistently predicted increases in delinquency or victimization.

The gang organization literature that has relied on self-report methodology has been of particular value for advancing the research on gang organization by statistically connecting gang organizational features to behavior. Generally, self-report studies that have examined the relationship between gang form (organizational structure) and function (delinquency and victimization patterns) have concluded that individuals belonging to groups with more indicators of group organization are involved in more

delinquency and victimization than individuals belonging to groups with fewer indicators.

Criminal justice data and gang organization.

The third methodological approach to studying gang organization is the use of official criminal justice data. Official criminal justice data generally is collected from surveys of law enforcement agencies or for criminal justice purposes.

The best example, at the national level, comes from the National Youth Gang Center. The National Youth Gang Survey is a nationally representative survey of law enforcement agencies across the United States (National Youth Gang Center, 2009). These law enforcement surveys have provided a resource that enables researchers to compare gang problems across jurisdictions. Researchers have used such surveys of law enforcement officers to create gang typologies in order to capture the structural differences of gangs. One of the most important structural typologies (Klein & Maxson, 1996) was based on law enforcement survey data, although many other typologies were not.

Instead of placing a gang on an organizational continuum, these studies identify different “types” of gangs. Typologies have existed since ethnographic research began in the early 20th century (Thrasher, 1927). More typologies have been created over time, but the reasons behind some of their categorizations have not always been clear. Some typologies have been based on organizational structure, some on the behavior of gang members, and some on a mixture of the two. Summarizing the typologies of the time, Klein (1971) argued that they ought to be structural, and he set out to identify four dominant patterns in gangs based on age, structure, territory, and longevity. Generally,

behavioral typologies have fallen out of favor, given Klein's (1995) finding that gangs are involved in "cafeteria-style offending" -- that is, gangs do not tend to focus on a singular type of crime, but they engage in many different types, from property crime to violent acts.

It could be argued that many of the earlier typologies have not been convincing, as researchers continue to discard them for new and different ones. The goal here is not to present a comprehensive review of all the different gang structural typologies that have been proposed, but simply to show that typologies are one way in which researchers have documented the variation in organizational structure among gangs. The purpose of typologies, as Fagan (1989) has suggested, is to help identify a common structure that can be found among gangs in different locations.

To be clear, not all typologies have been developed using official data. The most recent and influential gang structure typologies, however, came from Klein and Maxson (2006), who based them on a survey of law enforcement agencies. The authors developed a somewhat flexible typology consisting of five gang types: traditional, neo-traditional, compressed, collective, and specialty. These types were differentiated based on whether the gang had subgroups, number of members, members' age range, duration, territory, and crime versatility. The five gang types outlined by Klein and Maxson are as follows:

1. *Traditional gangs* have generally been around for more than 20 years, and the age range of the members is wide (from 20 to 30 years). Traditional gangs are large, having more than 100 members, and typically have subgroups. This type of gang is territorial and engages in a variety of criminal activities.

2. *Neo-traditional gangs* are typically less than 10 years old with no distinct pattern in the age of the members. Neo-traditional gangs generally have more than 50 members and have subgroups. Like the traditional gangs, they are territorial and engage in a variety of criminal activities.
3. *Compressed gangs* are typically less than 10 years old, and the members are within 10 years of age of one another. They are small groups of fewer than 50 members and do not generally have subgroups. Compressed gangs may or may not be territorial, and they engage in a variety of criminal activities.
4. *Collective gangs* generally range from 10 to 15 years in age, and the members' age range is likely to span more than 10 years. The collective gang will have more than 50 members and will not have subgroups. Like compressed gangs, collective gangs may or may not be territorial and they engage in a variety of criminal activities.
5. *Specialty gangs* are typically less than 10 years old, and the members' age range is smaller, spanning fewer than 10 years. Specialty gangs are small with fewer than 50 members and do not have subgroups. They are not generally territorial, and they specialize in one type of criminal behavior.

The Klein-Maxson typologies are not directly related to the formal-rational/informal-diffuse spectrum discussed above, but are an alternative approach to categorizing street gangs. Collecting data from 59 cities across the United States, the authors were able to fit most gangs into previously defined categories. The authors then examined each type of gang, comparing them based on average monthly arrests. They

found that traditional gangs accounted for the most arrests (10.9 per month), followed by neo-traditional (9.2 per month), collective (7.4 per month), compressed (6.1 per month), and specialty (5.7 per month) gangs. These findings re-affirmed previous findings that gang structure is related to gang criminality. Note that not all gangs fit perfectly into the categories that were created by Klein and Maxson. There were some instances in which gang experts were unable to categorize a specific gang, but the authors were able to “make the typology fit.”

In addition to surveys of law enforcement agencies about gang organization, a handful of studies have documented the social structure of gangs through case studies of law enforcement investigations (McGloin, 2005; Morselli, 2009; Rostami & Leinfelt, 2011). These studies used law enforcement intelligence from ongoing cases and interviews to construct networks of individuals. Key players within the networks could then be identified, and they were targeted for intervention or suppression.

In Newark, the North Jersey Gang Task Force conducted 32 semi-structured interviews to build a network for analysis. McGloin (2005) found that overall the gangs were loosely connected, but with pockets of cohesion. The gang network was comprised of unconnected subgroups instead of being one large connected network structurally. Further, the author found that a number of individuals in the network were important “cut-points” - important investigative targets for disrupting the network. McGloin’s work showed the benefit of using social network analysis to understand gang organization.

Similarly, Morselli (2009) offered case studies in the use of social network analysis. In one such study of an investigation of the Hell’s Angels, electronic surveillance was used to track associations between individuals. Morselli found variation

in network positions. The most reputable individuals in the network² did not have the *most* connections, but they did hold strategic positions; thus, they had high betweenness centrality. In another case study of a criminal investigation, Morselli found that gang members were not always the most important individuals (importance defined as high brokerage capital) in the network. They were, however, more likely than non-gang members to be facilitators for drug traffickers. Morselli's work highlights the importance of law enforcement data in understanding the organization of criminals generally and of gangs specifically.

Finally, a similar strategy was used in Stockholm as part of the Stockholm Gang Intervention and Prevention Project (SGIP) (Rostami & Leinfelt, 2011). SGIP collected information from different partners to construct a social network of gang members and gang associates. Connections were established through confidential information, project partners, and law enforcement agencies. The specific data that were used to make connections between individuals were not outlined. The information was used to identify individuals appropriate for intervention and suppression approaches. The authors do not directly address how decisions were made to target specific individuals. Nevertheless, the project was an important applied research milestone, because SGIP used social network analysis to identify appropriate interventions based on position within the network. More information is needed about the consequences of network positions to inform these types of projects.

² The reputable individuals in the network were those who were full patched members (Nomads/Rockers) in the biker organizations.

Limitations of prior gang research.

The three traditional methodologies for understanding gangs, gang members, and gang-related problems (i.e., ethnographies, self-report surveys, and official/law enforcement data) have, at times, produced different conclusions. The progression and advancement of gang research has often been hindered by the lack of availability of valid and reliable data sources. Given that deficit, comparative gang research has been sparse (Klein, 2005). The literature has been beneficial in connecting gang organization to behavior—that is, in connecting form to function; however, this body of literature still has a number of limitations.

Ethnographic and other qualitative methodologies have offered researchers valuable insight into gangs. This type of research cannot be generalized, however, and each study is limited to a few different gangs at most. The general conclusion from this growing body of literature is that, with some exceptions, gangs are unorganized (Decker & Van Winkle, 1994). Ethnographies and other qualitative methods can suffer from selection bias and other forms of methodological bias (Hughes, 2005). Ethnographers tend to examine unique gangs in large cities. The process is generally time-consuming and, as a result, it is difficult to generalize the findings. Still, ethnographies and other qualitative methodologies are valuable in that they bring context to the unique organization and social structure of gangs.

Gang research using self-report methodologies has been limited because of the variety of indicators used to assess gang structure (e.g., leadership structure, insignia, gang name, gang composition). Related, this body of literature has largely relied upon summarizing these indicators to assess level of structure, and this has limited researchers'

capacity to examine the dimensionality of gang structure and its impact on gang behavior (Pyrooz et al., 2011). Additionally, prior research has relied on individual perceptions of the study group's organization instead of using a direct measure of structure (Decker et al., 2008; Bjerregaard, 2002; Sheley et al., 1995; Pyrooz et al., 2011; Esbensen et al., 2001). It is clear that gang organization is not a dichotomy. Gangs vary in their levels of organizational structure, and research should continue to find ways to measure exactly how they vary. Measuring gang organization on a continuum has produced some important results (Decker et al.), but much remains to be explored in terms of the relations between form and function.

Finally, there are limitations to surveys of law enforcement and the data that are derived from them. With typologies, the challenge is that not all gangs fit into a specific typology. Additionally, too little is known about the consequences (criminal behavior) and development of the typologies that have been proposed. Another concern with gang typologies is that the measures by which they are categorized have not been well defined. It is unclear which factors are attributable to criminality, as the measures used are not always conceptually similar.

Additionally, law enforcement investigation case studies have offered valuable insight into the social structure of the gang. There are two limitations to law enforcement case studies, however. First, the data collected are unique to those investigations, and it would take a special investigation to replicate them in other jurisdictions. Second, the selection of individuals who belong within the network is not systematic; it is determined by law enforcement for specific reasons that cannot be assessed. While this is logical for

an investigation, systematic selection criteria are required for research to be replicated and generalized.

One persistent finding spans the three methodologies: Gang subgroups are important to the function of the gang. As early as Thrasher's 1927 work, researchers have found that members tend to hang out with small groups of other members and not with the entire gang. Thrasher found that over 60% of subgroups had fewer than 20 members. Decker and Van Winkle (1996) found that subgroups were typically between two and ten members and were important for criminal activities. These subgroups are the functional components of gangs, since the gang rarely acts as a singular unit (Klein, 1995). More recently, McGloin (2005) found that gangs in Newark were organized into small subgroups, as well.

More research is needed to understand how gang subgroups are socially organized and the importance of their composition. There are still unanswered questions surrounding group-level structures and processes of gangs. To better understand groups and gangs specifically, researchers should rely more on theories that conceptualize the mechanisms through which group structures matter.

Social Cohesion and Social Learning Theories

Group structure matters. A number of theories hypothesize the mechanisms of *how* group structures matter. Specifically, two theories have helped to identify the mechanisms that connect social structure and crime: social cohesion theories and social learning theories. Social cohesion theories address how groups vary in their levels of connectivity. Some groups are highly cohesive while others are sparsely connected. The collective identity that develops as a result of cohesion makes the group matter,

regardless of the individuals. Second, social learning theory addresses how individuals adapt behavior based on the composition and structure of their social networks. Individuals are influenced by those in their social networks, and it is through this learning process that social networks affect levels of crime.

Social cohesion.

Social structure and interaction have long been important concepts in sociology and criminology, and they have been incorporated into many leading theories. Social interaction, for example, has been a fundamental concept embedded within theories such as social capital (Coleman, 1988), informal social control (Sampson, Raudenbush, & Earls, 1997), and collective efficacy (Sampson et al.). Recognizing the linkages between people (i.e., social networks) has long been recognized as important for understanding the function of society (Durkheim, 1949). Cohesion is not always beneficial for society; there are supportive networks, but also networks that come together with malicious or criminal intentions, such as delinquent groups and gangs. Thus, the context in which cohesion occurs cannot be discounted. It is essential for researchers to understand both cohesion's role and its meaning in a variety of different contexts (Entwistle, Faust, Rindfuss, & Kaneda, 2007).

The notion of social cohesion, or the interconnectedness of individuals, dates back to Durkheim's (1949) concept of solidarity. The study of social cohesion has been a moving target, with much of the confusion having to do with the complexity of the reciprocity between the individual and group levels (Friedkin, 2004). Social cohesion has classically been defined as the "field of forces" that draws individuals toward a group and gives them the desire to remain in the group. As a causal model, Cartwright (1968) stated,

“the members of a highly cohesive group, in contrast to one with a low level of cohesiveness, are more concerned with their membership and are therefore more strongly motivated to contribute to the group’s welfare, to advance its objectives, and to participate in its activities” (p. 91).

Networks and cohesion have been found to co-vary with contextual factors in recent research (Entwisle et al., 2007). Entwisle et al. found that the variability in the structure of social networks provided the basis for understanding the contextual effects. The important finding from this research is that cohesion, measured by networks, varies in important ways. We cannot assume that classrooms, schools, neighborhoods, or villages that look the same will have similar network structures. Entwisle et al. concluded that “had we simply studied one village as ‘typical’... we would have had a very limited, and possibly misleading, picture” (p. 1524). This would likely be true of any study that examined the network structure of similar units. For gangs, or any defined group, the ideal measure of social cohesion is the relational structure of the entire group (Entwisle et al., 2007; Klein & Crawford, 1967).

Social cohesion has also emerged as an important consideration in gang research (Klein & Crawford, 1967), although researchers have not made many advances on the topic over the last few decades. Klein and Crawford examined how gang cohesion was related to delinquent behavior and found that the two were positively related. The authors noted that gang cohesion would develop as a consequence of normal group processes, and that external threat (e.g., gang rivalries) would be an important factor for increasing gang cohesion. In order to measure gang cohesiveness, the authors suggested that researchers measure gang member interactions and not rely on self-reported information.

In their study, they used data obtained from detached workers who observed and recorded interactions between gang members (p. 70). Gangs are ideal for social network techniques, given their self-bounded structure. Network techniques would add valuable contributions to the body of literature on gang cohesion and its relation to delinquency and crime.

Essentially, social cohesion exists when group-level structural conditions that produce positive member attitudes are present, and interpersonal interactions are able to maintain these group-level structural conditions (Friedkin, 2004). In social network terms, gangs that have higher density and show more evolution towards connectedness (i.e., reciprocity and transitivity) also have higher group-level cohesion. At the individual level, those who hold key or central positions in the gang are agents of influence in the gang.

Social learning, homophily, and delinquency.

Similarities between youth and their friends, whether behavioral or attitudinal, have been well documented in the gang literature (Snijders & Baerveldt, 2003; Burk, Kerr, & Stattin, 2008). The finding that delinquent youth act together also has been well documented, starting as early as Shaw and McKay (1931). The process through which individuals become similar and behave in similar ways, however, has been the crux of much debate in criminology.

Two major theories have attempted to explain why individuals tend to have similar levels of delinquency as their friends. First, past research suggests that individuals prefer similar others; that is, “birds of a feather flock together.” It is the notion that delinquents are similar in behavior to their friends because they have selected these

friends by looking for a mirror of their own behavior. On the other hand, differential association, or social learning theory, posits that the similarity measured is the result of individuals learning from one another and becoming more similar. More recent research has attempted to integrate the two theories, suggesting that both are at work in different situations. The current section will give a brief overview of the two opposing theories.

Selection theory proposes that people have a tendency to develop relationships with others who are like themselves. In social network terms, homophily is frequently observed in informal groups (McPherson, Smith-Lovin, & Cook, 2001). One's social characteristics can translate into social distance. Research has found that social networks have substantial homophily based on age, sex, race/ethnicity, and education (Marsden, 1987). Additionally, the stronger the ties are in a network, the greater the homophily in that network (Fischer, 1982). Homophily in a personal network starts at an early age (Kiesner, Poulin, & Nicotra, 2003; Shrum, Cheek, & Hunter, 1988) and is consistent in many different settings and types of relationships (Kalmijn, 1998; Shrum et al.).

In the criminological literature, the selection process has been explained in several ways. Glueck and Glueck (1950) found that youth tend to select similar others, and the authors concluded with the now cliché phrase "birds of a feather flock together." Social control theory (Hirschi, 1969), and later self-control theory (Gottfredson & Hirschi, 1990), led to a similar conclusion: Those individuals who have low self-control and weak attachments will select similar others. The selection is based on the fact that the youth have been poorly integrated and will prefer others based on their similar level of self-control. The consequences of low self-control are "criminal and analogous acts" (Gottfredson & Hirschi). Thus, individuals will select others with similar levels of self-

control, and the observed similarity of delinquency between peers is due to this underlying attraction. Although selection of peers based on a previous condition such as low self-control has been supported, the alternative explanation—that youth are similar because they learn the definitions and behaviors—has also found favorable support.

Using differential association theory, Sutherland and Cressey (1974) suggested that delinquent behavior is learned through interaction, where values and know-how are passed on from one individual to another. Akers (1973, 2009) later advanced the theory to specify the mechanisms through which delinquent behavior is learned. Akers extended differential association theory in a number of ways, one of which was to emphasize the role of behavior, contending that individuals can learn through imitation. Learning theories have been extensively tested, and support has generally been positive. Social learning is the building block for the creation of social structure (Akers, 2009). A meta-analysis of 140 studies found social learning theory to be a consistent predictor of delinquency (Pratt, Sellers, Cullen, Winfree, & Madensen, 2009). It is generally recognized that to some extent both the selection and influence processes are taking place, thus researchers have attempted to integrate the two theories.

Some examples of the integration of the selection and influence processes can be found in Thornberry's interactional theory (Thornberry et al., 1994), Matsueda's differential social control theory (Heimer & Matsueda, 1994), and Krohn's social network framework (Krohn, 1986). For example, interactional theory suggests that the process is bi-directional, and that associating with delinquents can increase one's own delinquency, but will also bring one into contact with other delinquents (Thornberry et

al., 1993). Thus, both selection and influence take place over time. Given this prior research, one would expect both processes to be active in social structures.

The gang literature has followed a similar line of research for understanding gang membership and delinquency, with the added dynamic that the peers are gang members. So the question is not only whether youth select one another and then further influence each other, but also how do these processes relate to gang members?

Selection, facilitation, and enhancement in gang research.

Thornberry et al. (1993) presented a framework of three explanations to understand the relationship between gang membership and increased delinquency. First, the concept of selection posits that individuals who join gangs share an individual deficit that makes them more likely to be criminal or delinquent. From this point of view, gangs are merely a collection of already delinquent-prone youth. Second, the facilitation explanation asserts that membership in a gang influences delinquency. The group dynamics, and the structure and culture of the gang, result in increased levels of delinquency by gang members. Last, the enhancement explanation combines both selection and facilitation. It suggests that gangs draw individuals who are more likely to be delinquent and then, as a product of the gang's structure and processes, already high offending rates will increase even further as a consequence of joining a gang.

The research on these explanations has generally concluded that “there is a minor selection effect, a major facilitation effect, and no evidence consistent with a pure selection model” (Krohn & Thornberry, 2008, p. 147). Some of the most recent examinations, those that controlled for selection effects and used a number of different data sets and analytic strategies, have found evidence of facilitation. For example,

Thornberry, Krohn, Lizotte, Smith, & Tobin (2003) found that the effect on delinquency of being a current gang member was about two and a half times greater than the effect of being a former gang member.

A series of studies were conducted through the Montreal Longitudinal Study of Boys (Haviland & Nagin, 2005; Haviland, Nagin, & Rosenbaum, 2007, 2008; La Course, Nagin, Tremblay, Vitaro, & Claes, 2003) that examined different violent offending and developmental trajectories. These studies found that the facilitation effect remained. Researchers using the National Longitudinal Study of Youth (Bjerk, 2009) and the Pittsburgh Youth Study (Gordon et al., 2004) also found support for the facilitation effect using a variety of delinquency outcomes. This individual-level finding has also been supported by community-level analysis (Tita & Ridgeway, 2007). The authors found, after matching communities on structural-level factors, that the gangs studied were facilitating crime.

The evidence to date suggests that gang membership increases one's involvement in delinquency (i.e., evidence of a facilitation effect). There are a number of explanations for this increase. At the individual level, gang members opt into gangs and are influenced by their members. At the group level, the social cohesion facilitated by the gang allows its members to form a collective identity on behalf of which they can act. It is important at the group level to identify the network structures that indicate increased cohesion and relate to more problematic gang behavior. The literature shows that social networks are important for understanding gang organization, and they allow researchers to better understand how structure is related to behavior. In order to further expand our

understanding of gangs and social networks, researchers must seek innovative methodologies and find new ways to analyze data that already exist.

Social Networks and Gangs

More than just a set of tools, social network analysis is a “broad intellectual approach” (Wellman, 1983, p. 156). Social structure gives individuals access to resources, both material and intellectual. Further, one’s network of associations determines the opportunities that one will have access to (Granovetter, 1973) and constrains the behaviors that a person may engage in. In order to better understand the nexus between social networks and gangs, this section will be divided into three subsections. First, I will explore the meaning of social networks for gang research. Social network analysis can help us to reconsider how we conceptualize and measure gang organization in a number of ways. Second, I will briefly explain social network analysis and present the advantages of using the network approach. Third, I will review prior research examining delinquency and gangs using social network analysis.

Gangs and the meaning of social networks.

Gangs are more than just the sum of the individual ties between the members. There is something unique about a gang that increases its members’ involvement in criminal activity (Thornberry et al., 2003). Fuhse (2009) points out that the structure of a network is based on meaning, and the meaning of a network is thus revealed in the structure that follows. That is, the structure that forms does so for a reason. Important to the construction of a group identity is the presence of opposition (Klein, 1995; Sanchez-Jankowski, 1991; Fuhse, 2009). The construction of meaning—name, symbols, roles,

expectations—emerges in response to the social environment and the repeated transactions that individuals have with one another. The identity that forms gives the network meaning. Once a collective identity has formed with a name and special clothing, symbols, and colors, the individuals in the network can act in the name of the collective (Fuhse, 2009). Gang members are then influenced to commit gang-motivated crime.

The content of the network is notably important. For gangs, the outcome of the collective might be crime, while for other groups the outcome might be something pro-social. This collective identity is likely the reason for the finding that the gang becomes the “dominant socializing institution” for many gang members (Vigil, 2002, p. 24). It is theorized that this collective identity and the group-level phenomenon are what make gangs unique.

An essential part of understanding the function of gangs is to understand their internal connectivity. The internal construction of a gang has meaning, and the network structure of a gang can tell us much about the social processes of a specific gang. At the group level, the gang literature has long recognized that the gang’s system of relationships matter. For instance, Vigil (1988) points out that gang members “prefer to spend idle moments with their closest friends” (p. 95). Further, Klein & Maxson (2006) state that the “tightness is in the cliques or subgroups, not in the overall gang structure” (pg. 199). Thus, by identifying which members are closest and how the network is structured, much of the meaning behind the network will be revealed. Gangs are more than a series of ties. They have social meaning and, as with all networks, that meaning “crystallizes and evolves in the course of transactions” (Fuhse, 2009, p. 68).

A number of important network structural elements appear to be relevant to gang organization. Prior research has shown that at the individual level structural position is directly related to involvement in gang behavior. The difference between core and fringe members has direct implications for behavior (Klein, 1995). Core members are more involved in formal gang activity, more likely to be arrested, more violent, and their delinquent careers start earlier. (Note, however, that one's position in the gang cannot be predicted by family structure, family income, or residential origin [Klein & Maxson, 2006]). Yablonsky (1962) uses the metaphor of an artichoke to depict gang involvement; one must peel off the outer layers (fringe) to get to the heart (core). Others propose that there are four positions that one can occupy within a gang: hard core, inner core, outer fringe, and fringe-fringe (Klein, 1971). The position that one occupies is usually defined by the gang member's involvement in gang activities and by the number of friends he or she has in the gang. Social network analysis provides the tools for identifying the positions that one might occupy within a gang.

In a related line of research, researchers found that gang membership increases criminal behavior because it increases criminal embeddedness (Bernburg, Krohn, & Rivera, 2006). More recently researchers have further developed the theoretical construct of embeddedness by the study of roles and positions that individuals have within a gang, referred to as gang embeddedness (Pyrooz, Sweeten, & Piquero, 2012). Pyrooz et al. (2012) examined gang embeddedness using self-report data. An item response theory model was used to examine five indicators of gang embeddedness: (a) frequency of contact with the gang; (b) position in the gang; (c) importance of the gang to respondent; (d) proportion of friends in the gang; and (e) frequency of gang-involved assaults. The

major finding from their study was that those who were more embedded in the gang desisted more slowly out of the gang. Important to the current study, gang embeddedness incorporates more than just the social position of an individual; it includes the qualitative assessment of the importance of the gang to the individual. Gang embeddedness is multi-dimensional, having to do with individual and group identity, social networks, and interpersonal dynamics. Centrality, the social network measure used in the current study, is perhaps just one dimension of embeddedness. This issue will be further discussed in the conclusion of the study.

Overview of social network analysis.

Social network analysis explores the relations among individuals, neighborhoods, organizations, countries, or anything that conceivably can be connected. One of the key characteristics of social network analysis is that it assumes interdependencies among people (Wasserman & Faust, 1994). This approach offers valuable perspective for understanding gang organizational structure, given that gang members do not act alone (Klein & Maxson, 2006). Traditional linear statistical modeling assumes independence (Berry, 1993), which can be problematic when attempting to understand relatedness. When we assume independence among individuals, we are essentially arguing for an “attribute” approach to understanding a given issue. In the case of criminology, when we use models that assume independence, we argue that individuals have characteristics, beliefs, attitudes, or something else that makes them more or less likely to engage in a particular criminal or delinquent behavior. From this research perspective, we have discovered that the *number of delinquent friends* is one of the strongest predictors of

delinquency among youth (Warr, 2002). This finding tells us that the fabric of one's social network matters. Further, Haynie's (2001, 2002) research suggests that the density of a person's network matters in terms of delinquency.

In social network analysis, the patterns of relations are directly measured, and the interdependencies are not discarded, but viewed as being an important piece of the puzzle. How relations are structured reveals the social position of the individuals in that network. Triadic closure, which exists in the natural evolution of a social network, is an example of this (Wasserman & Faust, 1994). Triadic closure refers to the increasing closeness of relationships among three individuals: A, B, and C. Transitivity (a form of triadic closure) is when A and B are friends, and B and C are friends, and then A and C become friends, resulting in the closure. Transitivity is exemplified by the phrase "a friend of a friend is a friend." We have all seen this happen in our friendship networks—friends are introduced through a mutual friend. There are circumstances, however, when A and B are close and B and C are close, but A and C will not become close. For instance, if A and B are married and B and C are having an affair, we are not likely to observe triadic closure. This is a brief example of how social structure can tell us something about the network. While the above was an example of three individuals, we can also learn from systems of relations between hundreds of individuals.

Many social network approaches have not been explored methodologically or theoretically in criminology or within the gang literature. In terms of criminology, Papachristos (2011) points out that "criminology would greatly benefit from understanding how the structure of networks and people's position in them relate to levels of criminality and victimization" (p. 10). Recently, social network analysis has led

to some exciting and informative findings for criminology as a whole, and for gang research specifically.

Social network analysis in criminology.

Social network analysis provides an alternative means of measuring and understanding group-level structure and the roles that individuals play in groups (Haynie, 2001; Snijders, Steglich, Schweinberger, & Huisman, 2009). As a group, researchers have found that gang members tend to be more delinquent than non-gang members, and most research suggests that their involvement in the gang directly contributes to their increased delinquency (Thornberry et al., 1993). Further, researchers have consistently found that one's social network matters for delinquent behavior (Haynie, 2001, 2003). Krohn (1986) argued that "structural characteristics of a personal social network affect the degree to which participation in the network constrains behavior" (pg. 581). Social networks and the position one occupies have direct implications for the level of delinquent activity at the group level as well as at the individual level.

Social networks at the group-level.

Some important group-level research has been conducted on gang relationships, cohesion, and distance using social network analysis. Researchers have examined the relationships between gangs (using the gang as the node, and not the individual), and have determined that the relations between gangs persisted over time, despite member turnover (Papachristos, 2009; see also Fleisher, 2006; Radil, Flint & Tita, 2010). In addition, McGloin (2005) found that knowing the level of cohesion for a gang is important for law enforcement intervention: Gangs that are more cohesive will respond more favorably to collective accountability approaches. Recent research has also found

that social distance and geographic distance are both important when evaluating the factors that promote or constrain gang behavior (Radil et al.; also see Schaefer, 2012). This research indicates that not only do gang members have relations with other members, but gangs have relations with each other as well (McGloin).

One framework that has been used to understand the perpetuation of violence between groups is the process of social contagion. The social contagion thesis posits that “sociocultural phenomena can spread through, and leap between, populations more like outbreaks of measles or chicken pox than through a process of rational choice” (Marsden, 1998, p. 68). Among other things, this theory has been used to understand the spread of violence among gangs (Papachristos, 2009; Decker, 1996). Important for the current study, violence can spread as a social contagion through the process of generalized violence (Jacobs, 2004). This is the process of violent acts being committed in order to restore one’s social position or to “save face.” The violent act need not be carried out against an actual perpetrator, but instead, innocent victims are allowed to represent those who may have wronged the individual in the past (Black, 1983; Jacobs & Wright, 2006). For instance, one gang member will shoot a rival gang member simply because he or she belongs to another gang. Papachristos, for example, found that gang homicides created a structure, or social network, through which violence moved. Violence was spread in order for gangs to maintain their dominance or status within the social structure. Papachristos’ research demonstrated that social networks are essential to understanding the perpetuation of violence that exists among gang members in the midst of a social structure.

Through the use of social network analysis, we can expand and explore more of a group's dynamics, especially how "gang or member interactions influence behavior, group processes, and community levels of crime" (Papachristos, 2006, p. 101). Prior research has shown that a gang's structural composition is directly related to involvement in gang behavior. Delinquency research and gang research make evident that one must account for the social network structure, both for statistical and theoretical reasons, in order to fully understand gang structure and the role of delinquency.

Social networks at the individual level.

Important individual-level research has also been conducted. For example, research using law enforcement intelligence has found that individuals vary in their level of connectedness to the gang (McGloin, 2005; Morselli, 2010) and that a person's centrality to the network is important (Morselli). Beyond how central an individual is, Morselli found "betweenness centrality" to be an important factor in determining an individual's role in the network. Betweenness centrality refers to the degree to which an individual lies between groups of individuals (Scott, 2000). A person who is a bridge between two groups might not be central to the overall network, but would have a high betweenness centrality. The importance of these findings was summarized by Fleisher (2002), who stated that "gangs are social networks composed of individual gang members," and that "gang member behavior is determined in part by a gang member's location in the structure of the social network. That location in the social network structure determines opportunities and constraints that expand or limit a gang member's choices" (p. 200).

Research has shown that social networks are important for gang structure, but more research is needed in order to identify the network elements and positions that impact gang behavior. Group dynamics and organizational structure have always been important concepts in gang research (Cohen, 1955; Short & Strodtbeck, 1965), yet social network methodologies have lagged behind in helping to inform this body of research.

In sum, social network analysis, both theoretically and methodologically, can inform the literature on gang organizational structure. The network approach examines the interconnectedness of individuals and how that interconnectedness matters. By connecting previously identified structural characteristics and continuing to identify network elements and locations that are important to gang function, the network approach has the potential to advance our understanding of gang organizational structure at the group level and the role of specific network positions at the individual level.

Current Study

Data on gangs, gang members, and gang crime are often difficult to obtain. Ethnographic, self-report, and official data all have contributed to our current understanding of gangs, yet each comes with its own set of strengths and limitations. In terms of social network analysis, ethnographic research offered some of the first in-depth gang network studies; however, ethnography has proved time-consuming and difficult to compare across contexts.

Social network data also have been collected with self-report methods (Udry, 1998; Udry, Bearman, & Harris, 2009), but self-report research presents challenges for obtaining access to gang members in a group or network. For example, self-report studies

have generally been school-based, where it is not always possible to identify a gang member's complete social network because gang members are much more likely than other students to skip and drop out of school (Thornberry et al., 2003). Not only do many self-report studies present network boundary issues, but the traditional way of measuring gang organization through self-report has limitations (Decker et al., 2008; Sheley, Zhang, Brody, & Wright, 1995; Bouchard & Spindler, 2010; Pyrooz et al., 2011; Esbensen et al., 2001; Bjerregaard, 2002).

Prior research suggests a need to explore different conceptualizations and measurements of gang structure in order to assess its impact on the behavior of gang members and on the gang as a whole (Pyrooz et al., 2011). Researchers have repeatedly found that the gang matters beyond the sum of its parts (Thornberry et al., 2003); however, the literature is lacking in knowledge of how a gang's difference at the group level produces behavioral and attitudinal differences. The thin conceptual framework in this body of literature contributes to unfocused research questions on gang organizational structure. One way to conceptualize and even operationalize gang organizational structure is to measure and compare the network structures present in the gang and to assess how they are related to criminal behavior.

Data collected by law enforcement agencies have the potential to be used to assess gang social structure. Many law enforcement agencies collect field interview (FI) cards on individuals with who they come in contact. The cards are then linked when a group of individuals comes in contact with the police. These data provide an opportunity to understand criminal networks generally, and gang social networks specifically.

The current study will address some of the aforementioned gaps in gang organization literature. First, the current study seeks to identify the *individual-level* network positions that are important in terms of network theory, and also to identify the network positions that are occupied by individuals who are more criminally active. Further, the current study will identify the *group-level* network structures that are prevalent in gang social networks. This will provide researchers with an alternative methodological approach to measure and analyze gang organization.

Research Questions

Three research questions will be addressed in the present study.

1. *Can relational data gathered from the police be used to examine social networks?* This study will convert official data into analyzable social networks, and in doing so will assess the strengths and limitations of official data for use in social network analysis. Specifically, what do gang networks look like when constructed from official data? How much membership turnover is there in gangs from year to year? Gang networks have been identified using police interview data (McGloin, 2005) and ethnographic techniques (Fleisher, 2002); researchers have not examined the functionality of official data and its utility to conduct social network analysis systematically, however.
2. *Are individuals most central to a social network those who are most criminally active and, related, what network positions most accurately identify the most criminally involved individuals?* Not only is the study interested in

the group-level effects, but also in whether social network analysis can identify individuals who are “most important” within the group. At the individual level, the overall connectivity of each gang member to the entire gang network will be identified. This will allow identification of those members who are most central to the network, those who are bridges between cliques, and those who are on the fringe of the network. Theoretically, knowing the relationship between an individual’s position in the network and that individual’s level of criminal involvement will offer new insights into social learning theory, identifying how network position is related to the diffusion of ideas and behaviors in criminal networks.

3. *What are the network structures that differentiate gangs, and are they related to group-level offending?* Klein and Maxson (2006) showed that gang structures are important for understanding the organizational sophistication of gangs. In terms of theory, the research questions will shed light on gang cohesion. Specifically, by quantifying the characteristics of the gang, this research can identify the stability of the gang and establish whether or not gang social structure and the criminal behavior of the group are related.

CHAPTER 3: METHODOLOGY

Setting

The current study takes place in Glendale, Arizona, a city located in the northwestern part of the Phoenix metropolitan area. Table 3.1 displays the 2010 Census estimates for the city of Glendale and the State of Arizona. Glendale had a population of about 226,721 in 2010, which was about 3.5% of Arizona's population. The median age of residents in Glendale was slightly less (32.5 years) than the state average (35.9 years).

In terms of sex, 49.1% of Glendale residents were male compared with 49.7% of Arizona residents. Glendale's percentage of racial and ethnic minorities was greater than the state average. Specifically, in Glendale, 51.5% of residents were Caucasian (non-Hispanic), 35.5% were Hispanic, and 5.6% were African-American, compared with the entire state where 57.8% of all residents were Caucasian, 29.6% were Hispanic, and 3.7% were African-American. About 16% of Glendale residents were foreign-born compared with 13.4% of all Arizona residents. Also, 10.5% of Glendale residents were non-U.S. citizens compared with 8.5% of all Arizona residents. About 12.6% of homes in Glendale were vacant in 2010, compared with 16.3% of homes throughout the state. Residents in Glendale were more likely to be renting their home (41.4%) than residents of Arizona as a whole (34%). Additionally, residents of Glendale were slightly less educated than the state average. Most noticeably, 19.1% of Glendale residents had less than a high school education compared with about 14.4% of all of Arizona residents. The median household income in Glendale was about \$45,669 compared with \$46,789 for Arizona. Last, the unemployment rate (11%) was higher in Glendale when compared with the state average (7.2%).

Table 3.1
2010 U.S. Census estimates

	Glendale	Arizona
Total population	226,721	6,392,017
Median age	32.5	35.9
% Male	49.1%	49.7%
Race or Ethnicity		
White (non-Hispanic)	51.5%	57.8%
Hispanic	35.5%	29.6%
Black or African American	5.6%	3.7%
American Indian and Alaska Native	1.2%	4.0%
Asian	3.8%	2.7%
Other race or ethnicity	2.3%	2.1%
% foreign born	15.9%	13.4%
% non-U.S. citizen	10.5%	8.5%
% of housing units vacant	12.6%	16.3%
% renter-occupied housing units	41.4%	34.0%
Educational attainment (residents over 25)		
Less than high school	19.1%	14.4%
High school	25.8%	25.1%
Some college	33.5%	34.6%
4-year degree or above	21.6%	25.9%
Median household income	\$45,669	\$46,789
% unemployed	11.0%	7.2%

Source: 2010 American Community Survey

In sum, when compared with Arizona residents statewide, Glendale residents on average were younger (median age 32.5 vs. 35.9), and more likely to be Hispanic (35.5% vs. 29.6%), non-U.S. citizens (10.5% vs. 8.5%), and unemployed (11% vs. 7.2%).

Additionally, compared to the average for Arizona, Glendale homes on average were less likely to be vacant (12.6% vs. 16.3%) and more likely to be occupied by renters 41.4% vs. 34%). Glendale households are likely to have an income that is slightly lower (\$45,669 vs. \$46,789).

Crime and gangs in Glendale.

Table 3.2 shows crime trends from 2005 through 2010 for the city of Glendale, the state of Arizona, and the United States. The data come from the Federal Bureau of Investigation's Uniform Crime Reports, thus reflecting only those crimes that were reported to law enforcement. During 2010, the violent crime rate (per 100,000 residents) in Glendale was 392.4 incidents per 100,000 residents, compared with 408.1 per 100,000 residents in all of Arizona and 403.6 per 100,000 residents in the United States. Violent crime is comprised of murder (and non-negligent manslaughter), forcible rape, robbery, and aggravated assault. The murder rate in Glendale in 2010 was 4.9 per 100,000 residents, compared with 6.4 per 100,000 residents in Arizona and 4.8 per 100,000 residents in the United States. The rate of forcible rape in Glendale was 18.7 per 100,000 residents, compared with 33.9 per 100,000 residents in Arizona and 27.5 per 100,000 residents in the United States. Robbery in Glendale occurred at a rate of 156.9 incidents per 100,000 residents, compared with 108.5 incidents per 100,000 residents in Arizona and 119.1 per 100,000 residents in the United States. Aggravated assaults in Glendale in 2010 occurred at a rate of 211.9 per 100,000 residents, compared with 259.3 per 100,000 residents in Arizona and 252.3 per 100,000 residents in the United States.

Property crime rates in Glendale in 2010 were higher for all types when compared with the rates in Arizona and the United States. Specifically, property crime rates in

Glendale were 5,513.3 incidents per 100,000 residents, compared with 3,534 per 100,000 residents in Arizona and 2,941.9 per 100,000 residents in the United States. When examined by category, Glendale had a burglary rate in 2010 of 922.6 per 100,000 residents, compared with a rate of 794.3 per 100,000 residents in Arizona and 699.6 per 100,000 residents in the United States. Larceny-theft rates were particularly high when compared with the rates of Arizona and the United States. The rate of larceny-theft was 4,049.1 per 100,000 residents, compared with 2,403.2 per 100,000 residents in Arizona and 2,003.5 per 100,000 residents in the United States. Motor vehicle thefts in Glendale occurred at a rate of 541.6 per 100,000 residents, compared with 336.5 per 100,000 residents in Arizona and 238.8 per 100,000 residents in the United States.

To better identify overall trends, Figures 3.3 and 3.4 show violence and property crime rates over time for the three geographical levels (i.e., Glendale, Arizona, U.S.). Figure 3.3 shows that violent crime declined over the 5-year period in Glendale, as well as in Arizona and the United States. In Glendale, violent crimes declined by 37% between 2006 and 2010. While property crime rates declined in Arizona and the United States over the 5-year period, Glendale's property crime rate increased by 13.3% over the same period. Additionally, thefts increased by almost 79% in Glendale from 2006 to 2010; Arizona and the U.S. experienced decreases in thefts over this period.

Table 3.2:

Crimes reported to law enforcement from 2006-2010 (rates per 100,000 residents)

	2006	2007	2008	2009	2010
Violent crime					
Glendale	619.1	602.1	518.2	449.7	392.4
Arizona	501.4	482.7	447.0	408.3	408.1
United States	473.5	466.9	454.5	429.4	403.6
Murder and non-negligent manslaughter					
Glendale	8.4	6.0	6.6	7.1	4.9
Arizona	7.5	7.4	6.3	5.4	6.4
United States	5.7	5.6	5.4	5.0	4.8
Forcible rape					
Glendale	30.2	23.2	25.7	21.2	18.7
Arizona	31.5	29.3	25.7	32.0	33.9
United States	30.9	30.0	29.3	28.7	27.5
Robbery					
Glendale	187.5	216.4	229.1	164.7	156.9
Arizona	149.6	151.7	149.2	122.8	108.5
United States	149.4	147.6	145.3	133.0	119.1
Aggravated assault					
Glendale	393.0	356.6	256.8	256.8	211.9
Arizona	312.7	294.3	265.9	248.1	259.3
United States	287.5	283.8	274.6	262.8	252.3
Property crime					
Glendale	4,865.1	4,972.0	5,234.6	4,896.1	5,513.3
Arizona	4,627.9	4,414.0	4,291.0	3,556.5	3,534.0
United States	3,334.5	3,263.5	3,212.5	3,036.1	2,941.9
Burglary					
Glendale	1,510.9	1,104.4	1,038.3	1,000.1	922.6
Arizona	925.3	912.2	868.9	809.8	794.3
United States	729.4	722.5	730.8	716.3	699.6
Larceny-theft					
Glendale	2,262.8	2,682.8	3,268.5	3,220.2	4,049.1
Arizona	2,813.1	2,738.4	2,849.5	2,352.8	2,403.2
United States	2,206.8	2,177.8	2,167.0	2,060.9	2,003.5
Motor vehicle theft					
Glendale	1,091.4	1,184.7	927.7	675.9	541.6
Arizona	889.5	763.4	572.6	394.0	336.5
United States	398.4	363.3	314.7	258.8	238.8

Source: FBI- Uniform Crime Reports

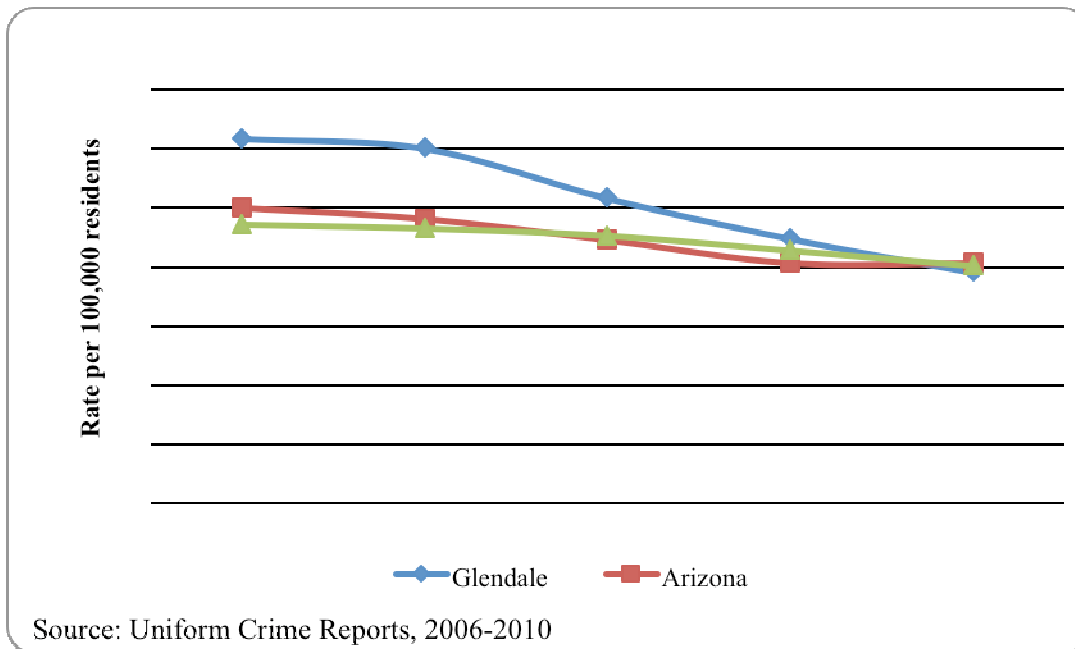


Figure 3.3. Violent crime rate by year

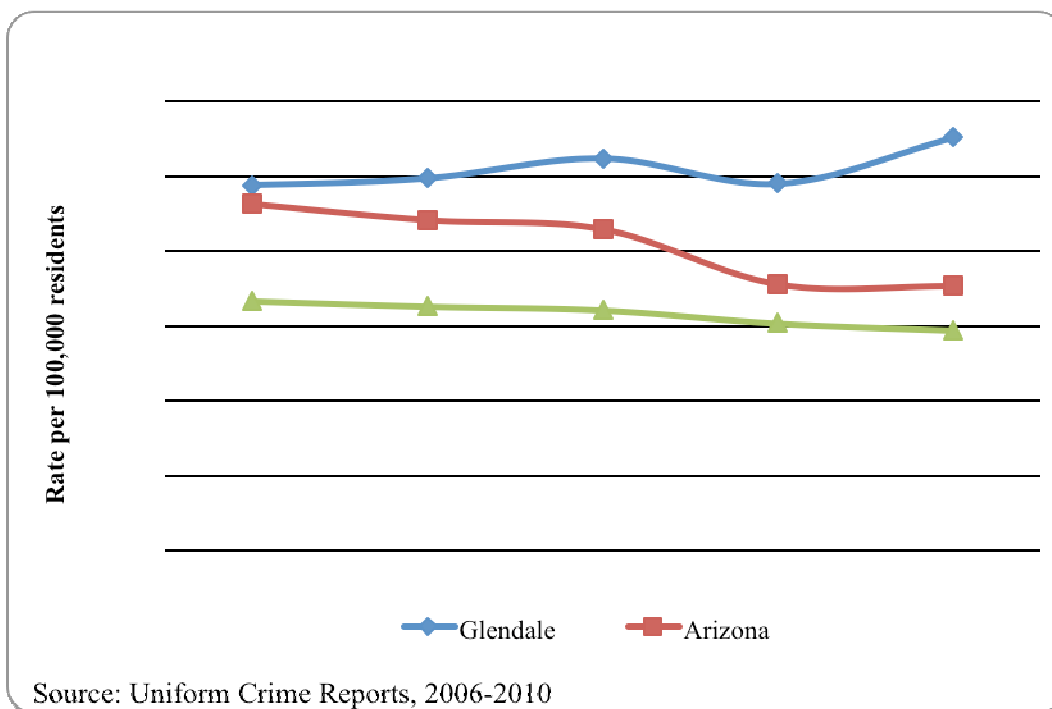


Figure 3.4. Property crime rate by year

To better understand the scope of Glendale's gang problem, I examined data from the National Gang Center's National Youth Gang Survey (NYGS). The NYGS has been conducted since 1996 and is an annual, nationally representative sample of law enforcement agencies. NYGS data have been found to be a reasonably valid and reliable source of gang data (Katz et al., 2012; Decker & Pyrooz, 2010). From 2005 to 2009, Glendale reported a gang problem in the city every year. Additionally, data from the survey indicated that on average there were 4.2 gangs and 283 active gang members documented in Glendale. Data from the survey also showed that Glendale had a dedicated gang unit to respond to gangs. The current study specifically examines the social structure of the three local street gang cliques in Glendale³: (a) the Varrio Sixty First (VSF 61), (b) Westside Grandel (WSG 63), and (c) Varrio Clavelito Park (VCP 52).

The Glendale Police Department (GPD) is the primary local law enforcement agency serving the city. In 2010, GPD had 407 sworn officers and 146 civilian employees. The department consisted of one chief, 2 assistant chiefs, 5 commanders, 17 lieutenants, 56 sergeants, and 321 officers and detectives. The department is recognized as an innovative agency that has been seeking better, more efficient ways to address crime. The most recent example is the department's Smart Policing Initiative, funded by the Bureau of Justice Assistance. From 2009 to 2011, and again from 2012 through 2013, officers were trained to use a problem-solving model (SARA) to proactively address thefts at convenience stores in the city. The department continues to look for innovative data-driven ways to address crime.

³ The NYGS data estimated more gangs than are used in this study because the current study only examined local street gangs. A number of other gangs in the city are the result of gang migration.

Data collection

Research on the validity of police-generated gang data has historically been mixed. Some of the most recent research indicates that such data accurately discriminate between those who are a greater threat to a community and those who are not (Katz, Webb, & Schaefer, 2000). Despite the obstacles that police agencies face in collecting gang data, police data is widely available and its collection continues. By acknowledging the challenges of using police gang data, researchers can be aware of its limitations and begin to think of ways to address its quality.

The data for this dissertation relied on official police data. Data collection for the present study took place from June 2011 through January 2012. The Glendale Police Department granted access to their databases, which they use to track gang members, field contacts, incidents, offenders, and other information relevant to the current study. Three data sources were used for the present study: (a) Glendale Gang Member Identification Card (GMIC) data; (b) official crime report data; and (c) field interview card data (FI cards). Data collection focused on a 5-year period from January 1, 2006 through December 31, 2010. Glendale GMIC data consisted of information on Glendale gang members documented by the police. The data included information about each individual's gang and associates. Official crime report data included every reported crime and/or when an individual was arrested. These reports provided details of the incidents and the events. Third, FI card data included information obtained during police officer contacts with individuals, but not necessarily when a crime had been committed. The police field interview cards documented where contact was made, with whom it was

made, and any other persons who were present during the contact. A thorough description of the three sources of data is presented below.

Gang Member Identification Card data.

GangNET is a statewide intelligence system used to track gangs, gang members, and their affiliates. The database is maintained by the Gang and Immigration Intelligence Team Enforcement Mission (GIITEM), under the direction of the Arizona Department of Public Safety. GangNET is used to document individual's names, aliases, nicknames and other monikers, and several personal descriptors such as sex, age, race, ethnicity, height, weight, hair and eye color, and date of birth. Additionally, data is collected on place of birth, school name, grade and contact information, employer name and contact information, home address, and phone numbers. Last and prior arrests, probation status, and details about gang affiliation can be included. The information contained in GangNET is collected through Gang Member Information Cards (GMIC) that are filled out by officers. A GMIC is initiated any time an officer makes contact with an individual who meets statutorily defined criteria for gang membership. The GMIC allows the officer to record information about the individual's gang affiliation, including that the membership criteria has been satisfied; the date on which the individual is to be removed from the system; and current membership, status, and position in the gang. Details about the individuals' gang and its name, the name of their clique, and the geographical scope or turf of the gang are also included.

In the state of Arizona, a gang member is statutorily defined by ARS § 13-105.8. Specifically, in order to be documented as a gang member in Arizona a person must meet at least two of the following statutorily defined criteria:

1. *Self-proclamation.* If a person admits membership to a gang or association with a gang, the self-proclamation criterion is met. Documentation of self-proclamation can come through criminal justice records or accounts from suspects, victims, or witnesses.
2. *Witness testimony or official statement.* Witness testimony that a person is a member of a street gang can come from court testimony, depositions, interviews, or from confidential informants.
3. *Written or electronic correspondence.* Any information that makes reference to a specific person's gang activity can come from letters, notes, tapes, or other documentation. Any written or electronic communication having to do with criminal investigation by a law enforcement agency that indicates a person's involvement in a street gang can satisfy this criterion.
4. *Paraphernalia or photographs.* This criterion can be met if an individual is in a photo or drawing that depicts gang membership or association. If the picture includes gang signs, colors, or other gang insignia, it satisfies the criterion for every person in the drawing or photo.
5. *Tattoos.* A tattoo qualifies for this criterion if it displays a gang moniker or symbol, regardless of whether the tattoo is old, covered, or burned out.
6. *Clothing or colors.* Gang type clothing or colors can be an indicator of gang membership; these can include rags, patches, belt buckles, bandannas, hats, vests, or other accessories.

7. *Any other indicia of street gang membership.* This criterion allows for law enforcement to identify new and innovative ways that gang members might represent their gang (ACJC, 2007: 3).

Information collected on documented gang members is uploaded into the statewide GangNET database. Based on the criminal intelligence system's operating policies (28 Code of Federal Regulations Part 23), GangNET data must be purged after 5 years with no new events.

After initial review, it was determined that not all GangNET data that had been collected had been entered into the intelligence system managed by the Department of Public Safety. Much of the data that had been collected by the police had not been entered and uploaded into the DPS system. The only way to retrieve the data was to go back to the data retained in hard-copy files. Given these limitations to GangNET, data from each of the completed Gang Member Information Cards (GMIC) were hand-entered to insure data integrity. The GMIC data were entered from May to November of 2011. The current study did not suffer from the limitations of purged data, since all information was hand-entered from the source paper files instead of downloaded from the GangNET system, which is purged on a regular basis in accord with federal regulations.

Official crime report data.

GMIC data were linked with official crime report data. Official crime report data are collected whenever a Glendale officer makes an arrest. Data fields collected as a result of the incident include the reporting officer's name; the name, type, and Arizona Revised Statute code for the reported offense; the location (address or cross-street), date, and time of the occurrence, with separate entries for start and end times; property

involved (value and whether stolen/recovered/damaged); medical information (physician, hospital, ambulance, mortuary, etc.); and whether the incident involved domestic violence. Individual characteristics collected include separate entries for each victim, suspect, witness, or other person, by type, and include the following fields: name (full personal or business); aliases/maiden/nicknames; date of birth; physical characteristics/description (race/ethnicity, sex, age, height, weight, hair color, eye color, clothing, scars/marks/tattoos); home address; email address; phone (home, cell, work, etc.); social security number; driver's license number and state in which it was issued; employer name and contact information; school (grade level and contact information); and relationship to suspect/victim. The department's electronically accessible CAD/RMS system was used as the mechanism for acquiring the official crime report data.

Field interview card data.

The above data were also linked with data generated through field interview (FI) cards. FI cards provide a brief record of police-public contacts, and are filled out when an officer makes contact with an individual, but does not make an arrest. FI cards collect information about the person in contact with an officer (i.e., the interviewee). The FI cards used by GPD collect information on the date, time, location, and nature of the contact; the individual's name, home address, phone number, age, race/ethnicity, sex, date of birth, height, weight, hair and eye color, social security number, driver's license number and state, birthplace (city and state), and employer (and contact information); and vehicle details (color, make, model, year, style, plate, state, VIN#). The cards also note any other persons who were present during the encounter. If two or more individuals were listed on the same FI card, I established a link between those individuals. The FI

cards provided the basis for constructing a relational database in the current study. The FI card data and the crime report data all were downloaded electronically in January 2012.

Data security.

The data collection procedure for the current project was approved by Arizona State University's Institutional Review Board (IRB Protocol # 1112007222). Initial data processing and management took place at the main station of the Glendale Police Department. The data were retrieved and consolidated from the various data sources using a computer housed at the GPD main station into a single merged file. Once all relevant data sources were combined in the merged file, individually identifiable variables (e.g., name, social security number, driver's license, date of birth) were deleted from the file, and a randomly generated numeric identifier was used in their place, creating a de-identified analysis file. The appropriate GPD personnel reviewed the analysis file to verify that the data had been effectively de-identified. The electronic file then was transferred to Arizona State University for further analysis.

The data were kept secure throughout the project. The Center for Violence Prevention and Community Safety (CVPCS) offices are located in a keycard entry, limited access office building at the downtown Phoenix campus of Arizona State University. The electronic files were located in a secure network environment, only accessible through user-id and password protected office computers. Throughout the project, there were no known incidents of identified data being released.

Sampling and data structure.

The current study used 5 years of data (2006-2010) from the three sources of official data described above. The sampling frame for the current project consisted of all

documented Glendale-based street gang members and any persons within two relational steps of association of a known gang member. Law enforcement agencies do not traditionally keep relational data sets in analyzable form; most data kept is based on an individual or an incident. For this reason, an analyzable relational dataset was constructed. The data collection process and the data organization for this sampling frame are described in detail below.

Before the process is described, it is important to clarify the structure of the data. Relational databases are structured differently than individual-level databases (used in most social science research). Relational databases display the relations between the individuals in the study; it is similar to a weights matrix used in community studies. The relational data first was collected as an edgelist and later was converted to a sociomatrix. An edgelist identifies an individual (first column) followed immediately by the identifiers of the person with whom they have a relationship (second column). A sociomatrix is an N by N matrix with every person listed as a row and a column. At the intersection of two individuals, a marker of 1 indicates a relationship, and a marker of 0 indicates the absence of a relationship between two individuals. Both edgelists and sociomatrices were constructed for each of the 5 years in the current study.

The current study established that two individuals were related if they were identified by the GPD as associating with one another through Field Interview cards. When the police in Glendale made contact with a person for any reason, they filled out an FI card; when two individuals were identified as associating with one another during a contact, the two FI cards were linked. Using this link between FI cards, the study could establish that two or more individuals were related.

Thus, the social networks constructed in this study reflect the relations that were identified by law enforcement. Additionally, the individual-level data collected were structured similarly to a traditional dataset. That is, each row represented an individual in the sample, and columns represented the characteristics of that individual. As a result, the present study uses both a relational and individual-level dataset for each of the 5 years in the study.

The construction of the relational dataset followed a systematic progression for each year. The first step in the data collection process was to obtain the list of documented gang members for each of the 5 years. This list was constructed by locating all of the Gang Member Identification Cards that were filed each year. The list of documented gang members provided the starting point for each of the 5 years. The documented gang members were called Step 0; from this step, relations were collected two steps out from Step 0, within each year. First, FI cards and the list of “known associates” on GMICs were examined in order to establish the relations among the documented gang members. For each linked FI card, a new row on the edgelist was constructed to represent that relation. The first step (Step 1) out from the gang members included all individuals who were identified through FI cards as associating with a documented gang member, but who were not themselves documented gang members. If a person was identified as associating with a gang member within a given year, that person was included in the sample and his or her relationship was recorded on the edgelist for that year.

Next, the second step (Step 2) was established as those individuals who were identified through the FI card as associating with a person from Step 1. Thus, those

identified in Step 2 were friends of friends of documented gang members. As a result of this process, for each of the 5 years studied, relational data were collected based on the documented gang members, as well as on the relationships extending two steps beyond the list of documented gang members. This strategy has been supported by previous research, which suggests that after two steps, the network begins to fold back onto itself (Frank, 2005; Papachristos, Braga, & Hureau, 2012).

One anticipated issue was matching individuals across datasets, both for the relational and individual-level information. Field interview card information is often incomplete and contains a substantial amount of missing data. A system was implemented to ensure that each individual was identified as the same person across years. At the point that a gang member or associate of a gang member was identified as one who would be included in the sample, that person was given a random number as an identifier. A separate dataset was constructed listing each person's identifier along with the available information; this ensured that no person would be double-counted and that each person's associates were identified accurately.

The information used to match persons included full name, date of birth, aliases, social security number, driver's license number, sex, and race/ethnicity. After the database (which linked all of the databases) was created, all individual identifiers were removed and the analysis file contained only the randomly generated numeric identifiers in the relational dataset to protect the identities of the subjects. The final dataset included all of the available demographic information (gang name, age, sex, race/ethnicity, and criminal history).

Data analysis was conducted in three stages. Each stage of analysis corresponded to one of the study's three main research questions. The overall objective of this dissertation is to understand how social structure is related to behavior. Specifically, it is to understand how social networks, as measured by FI cards, are related to criminal behavior and gang membership. The following sections will outline the specific analytic techniques that will be used to answer each of the three research questions.

CHAPTER 4: CREATING NETWORKS FROM OFFICIAL POLICE DATA

As discussed in previous chapters, prior research suggests that official police data could be useful for understanding the social structure of street gangs. Using existing police data to better understand gangs and criminal groups has the potential to inform both theory and policy. Police FI card data would seem to be a rich resource for understanding gang social networks, but unfortunately, little prior literature has examined its utility.

The purpose of this chapter is to determine whether relational data gathered from existing police FI cards can be used to understand the social networks of local street gangs. I approached this issue by converting GPD FI card data into graphic visualizations and examining network legibility, descriptives, and stability.

Analytic Strategy

In order to understand social networks (e.g., structures and positions), it is necessary to visualize the networks (De Nooy, Mrvar, & Batagelj, 2011).⁴ Similar to the visual examination of spatial data (i.e., crime hotspots), network visualizations give researchers a better grasp of the data. One of the unique benefits of network analysis is the ability to visualize network structure. One issue when graphing social networks is determining the layout of the network. Unlike geographic data, relational data does not have a predefined position or coordinate, and the position of an individual within the network visually can be important for describing the network. Although there is some

⁴ To assist the reader in the interpretation of the analysis, some important terms are defined in Appendix A. While these terms are general social network terms and those familiar with social network analysis will be familiar with them, their presentation is helpful to ensure understanding.

need to manually position individuals within a network, it is best to use an automated procedure in order to eliminate researcher bias (de Nooy et al.).

There are a number of goals when graphing social networks into sociograms. First, we want the distance between two individuals to represent their social closeness. This is similar to what we want from a geographic map, where we expect the distance between two cities on the map to correspond to the geographic distance between the cities. Although not as straightforward, the distance between nodes in a sociogram should represent social distance as accurately as possible. Second, the sociogram should be legible. That is, the aesthetics of a sociogram are important—lines representing ties should not be on top of each other, and nodes should not be bunched together to appear as one (de Nooy et al., 2011). A number of automated processes and algorithms have been created to more accurately depict the social distance between individuals and to increase legibility in a systematic and unbiased way. Exploratory network analysis for the present study relies on Pajek, which is a network analytics software program that provides a number of automated functions to help find the optimal layout for a set of nodes.

The creation of the sociogram often requires some minor manual adjustments. To prevent any patterns from developing because of researcher bias (e.g., a preconceived notion of the network's structure), the sociograms in this study will be presented through the Kamada-Kawai energy command (Kamada & Kawai, 1989). Energy commands pull nodes until they are in a state of equilibrium, balancing the distance between each node and those it is tied to, seeking the optimal sociogram based on the data. This particular energy command has been found to be one of the most stable, and as a result it has been used frequently (Kamada & Kawai, 1989; de Nooy et al., 2011). Additionally, since the

final visualization can depend on the starting point of each node, each energy command was run multiple times to ensure that the final visualization was stable. I will present network visualizations across the 5 years of collected GPD FI card data.

In addition to network data visualizations, the network descriptives will also be presented. For the purpose of the present study, the total number of nodes and ties by year will be examined along with the characteristics of the individuals in each network by year. I will also examine network stability over time.

Prior research suggests that gang members belong to their gangs for a relatively short period of time. For example, Thornberry et al. (2003) found that in Rochester, about 50% of gang members self-reported being in a gang for only a year or less, and almost 80% reported being in a gang for less than 2 years (Thornberry et al.). The current study will examine how long individuals continue to be a part of the gang social network. This is done by examining whether the same individuals are identified as part of the network for multiple years.

Findings

As described above, networks were constructed by year using GPD FI card data. Data collection was conducted through a 3-step process. For each year, data collection began with those individuals who were documented gang members. In social networking terms, this is referred to as step 0. The next step (step 1) included collecting data from all those individuals who associated with gang members. The last step (step 2) included all individuals who associated with those who associated with documented gang member (i.e., those identified in step 1).

Table 4.1 displays the descriptive statistics of those who were included in each year's network. In 2006, 94 individuals were included in the network, compared with 169 in 2007, 107 in 2008, 103 in 2009, and 121 in 2010. More than 80% of those included in the network each year were males. Specifically, the percentage of males ranged from a low of 82.7% in 2009 to a high of 91.3% in 2006. In terms of race and ethnicity, a large majority of those included in the network were identified as being Hispanic. For example, in 2006, 91.3% of those who were included in the network were Hispanic. This dropped slightly in 2007 to 83%, and then increased again to 93.6% in 2008, 91.8% in 2009, and a high of 94.2% in 2010.

For each given year, an individual could either enter the network as a gang member (through a GMIC) (step 0), as an associate of a gang member (step 1), or as an associate of an associate (step 2). In 2006, 48.9% were gang members, 46.8% were associates, and 4.3% were associates of associates. In 2007, 40.2% of those in the network were gang members, 50.3% were gang associates, and 9.5% were associates of associates. In 2008, 46.7% of those in the network were gang members, 48.6% were gang associates, and 4.7% were associates of associates. The proportions were similar in 2009, with 46.6% gang members, 47.6% gang associates, and 5.8% associates of associates. The final year of the study had the highest percentage of gang members, with 54.5% being gang members, 45% gang associates, and only 2.5% associates of associates. The low percentage of added individuals at step 2 in each year was consistent with previous findings that the network would start to fold in on itself after two steps (Frank, 2005), and that adding another step (step 3) was not methodologically necessary. This is because

network saturation has been achieved where the same individuals continue to be identified through the process and few new individuals are identified.

The documented gang members in the study all were associated with Grandel, the local Glendale street gang. Interviews with police officials indicated that there were three known cliques within Grandel: Varrio Sixty First (61), West Side Grandel (63), and Varrio Clavealito Park (52). The numbers, 61, 63, and 52 represented the cliques and indicated the streets where each clique was located. Across years, the 61 clique was the largest in the network, followed by 63 and 52. Specifically, the percentage of those in the network who were 61 members ranged from 18.3% in 2007 to a high of 24.2% in 2010. The 63 clique, the second most frequently documented Grandel clique, ranged from 11.8% of those in the network in 2007 to 18.3% in 2010. The least frequently documented clique of the three was the 52 clique, which ranged from 8.9% of those in the network in 2007 to 11.7% in 2009. There were a small number of gang members who were identified as Grandel members, but were of an unspecified clique. This group ranged from 0% of the network in 2009 and 2010 to 3.2% in 2006.

Table 4.1.
Individual descriptors by year

	Year				
	2006	2007	2008	2009	2010
Age ^a	23.34	21.08	22.44	25.85	23.91
Male	91.3%	87.2%	88.3%	82.7%	85.8%
Race or Ethnicity					
White	5.0%	13.5%	4.3%	5.1%	4.2%
Black	1.3%	2.0%	0.0%	3.1%	0.0%
Hispanic	91.3%	83.0%	93.6%	91.8%	94.2%
Other	2.5%	1.4%	2.1%	0.0%	1.7%
How they entered the network					
Gang member (step 0)	48.9%	40.2%	46.7%	46.6%	54.5%
Gang associate (step 1)	46.8%	50.3%	48.6%	47.6%	45.0%
Associate of associate (step 2)	4.3%	9.5%	4.7%	5.8%	2.5%
Gang name					
Non-gang member	51.1%	59.8%	53.3%	53.4%	48.3%
Varrio Sixty First 61	21.3%	18.3%	22.4%	18.4%	24.2%
West Side Grandel 63	13.8%	11.8%	13.1%	16.5%	18.3%
Varrio Clavalito Park 52	10.6%	8.9%	10.3%	11.7%	9.2%
Other Grandel	3.2%	1.2%	0.9%	0.0%	0.0%
Criminal Involvement ^a					
Arrested	57.4%	50.9%	49.1%	58.3%	59.5%
Violent offense	9.6%	6.5%	10.2%	8.7%	8.3%
Property offense	16.0%	18.9%	13.0%	19.4%	17.4%
Drug offense*	27.7%	21.3%	11.1%	15.5%	24.0%
N	94	169	107	103	121

^a Between January 1st and December 31st of the given year

In terms of criminal involvement as measured by arrest, individuals in the sample had a high likelihood of arrest within the year that the network was built (Table 4.1). The percentage of individuals in the sample who were arrested in a given year ranged from a low of 49.1% in 2008 to a high of 59.5% in 2010. Those arrests were for offenses other than violent, property, and drug offenses (e.g., disorderly conduct, fraud).

Looking at arrests by type of offense showed that individuals in the sample were most likely to be arrested for a drug offense, followed by a property offense and then a violent offense (Table 4.1). Of the three types of offenses, significant differences across years were found only for drug arrests; the percentage of those in the sample arrested for drug offenses was lowest in 2008 (11.1%) and highest in 2006 (27.7%). Those in the sample were more likely to be arrested for property crimes than for violent crimes. The percentage of the sample arrested for property crimes was lowest in 2008 (13%) and highest in 2009 (19.4%). The portion of the sample arrested for a violent offense was lowest in 2007 (6.5%) compared with and highest in 2008 (10.2%).

Table 4.2 displays the descriptive of the network by year. In 2006, there were 94 individuals in the network. Among these individuals, there were 96 associations or ties (an average of 1.02 ties per person) compared with 1.48 ties per person in 2007, 1.54 ties per person in 2008, 1.18 ties per person in 2009, and 1.16 ties per person in 2010. This indicates that each person, on average, was tied to just more than one other person. This seems low, but the average is brought down by the isolates in the network. The average number of ties per person is an indicator of the overall density of the yearly network; however, there was variation based on group within each year.

Related, within each year there were about 20 components. A component is a cluster of people who are connected, also called groups. The number of components ranged from 17 in 2008 to 22 in 2010. The number and size of the groups within the network is important. If a network was comprised of one large connected group, information and goods would flow more easily from one person to another. Since the networks in the current study were comprised of many smaller groups from year to year, it is more likely that information and goods (e.g., drugs, guns) would have taken longer to disperse throughout the network.

Table 4.2 also presents findings on group size. In 2006, the largest group was comprised of 16 people, which was 17% of the network in that year. In 2007, the largest group had 54 people, about 32% of the network in that year. In 2008, the largest group was 31 people (28.7% of the network); in 2009 the largest group had 19 people (18.4% of the network); and in 2010 the largest group was comprised of 21 persons (17.4% of the network).

Anyone who was not part of a group was considered an isolate. Isolates are individuals who are not found to be tied to anyone else in a network (Scott, 2000). The number of isolates each year ranged from 11.7% to 17.5% of the network. Specifically, 11.7% of individuals were isolates in 2006, compared with 12.4% in 2007, 12% in 2008, 17.5% in 2009, and 14.9% in 2010. Isolates are not actively involved in the social network. Given the process of building the network, all isolates are documented gang members. This might indicate that a certain percentage of documented gang members were no longer actively involved in the network.

Some of the components included members of more than one clique, as shown in Table 4.2. The percentage of groups that are hybrid cliques ranged from 5% in 2009 to 23.8% in 2006. At the individual level, the percentage of individuals who were in a hybrid group ranged from 17.9% in 2009 to 49.7% in 2007.

Table 4.2.
Network descriptives by year

	Year				
	2006	2007	2008	2009	2010
Number of people	94	169	107	103	121
Number of ties	96	250	165	122	140
Average ties per person	1.02	1.48	1.54	1.18	1.16
Number of components (groups)	21	19	17	20	22
Size of largest component	16 (17.0%)*	54 (32.0%)	31 (28.7%)	19 (18.4%)	21 (17.4%)
Number of isolates	11 (11.7%)	21 (12.4%)	13 (12.0%)	18 (17.5%)	18 (14.9%)
Percent of groups that are hybrid cliques	23.8%	21.1%	11.8%	5.0%	18.2%
Percent of individuals in hybrid clique groups	44.7%	49.7%	34.6%	17.9%	24.8%

* percent of the network

Figures 4.3 through 4.7 display the sociograms for each year. Each dot represents an individual in the network. Each line represents an association between individuals. As a reminder, the associations between individuals were derived from FI cards collected by the police. For each year, it is clear that there is not one cohesive network, but many disconnected groups. The figures are visualizations of what is shown in Table 4.2. The largest component (or group) can be found in the top left of each sociogram, and the isolates are those at the bottom of the sociogram (the dots with no lines to them). These visualizations show that there are many different structures across years.

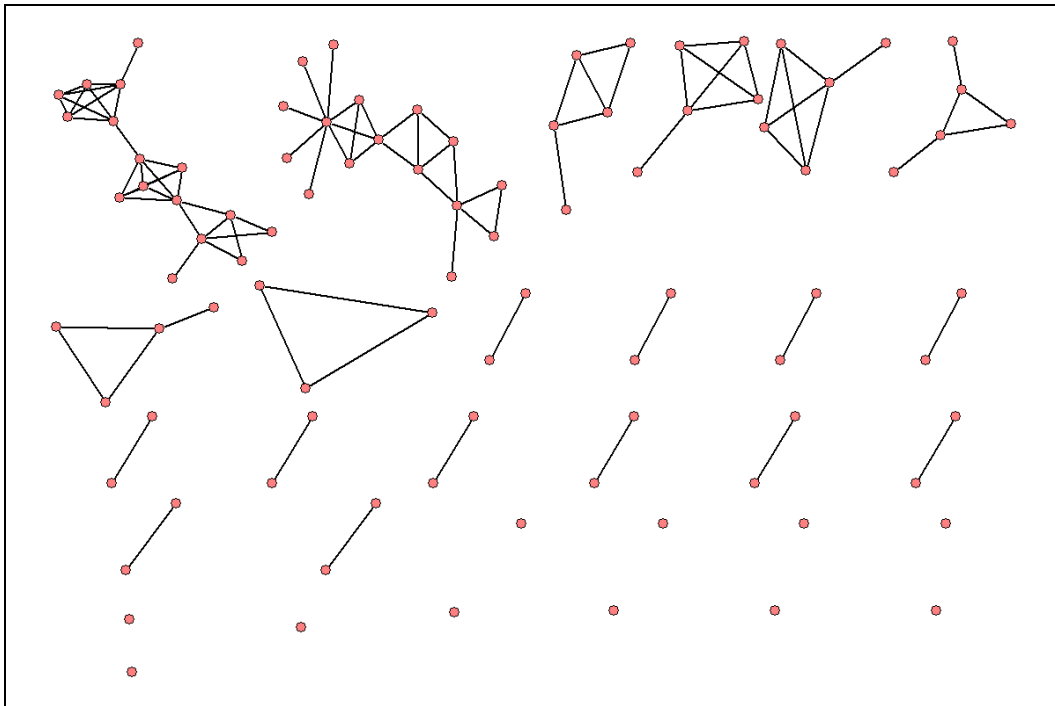


Figure 4.3. Social network in 2006

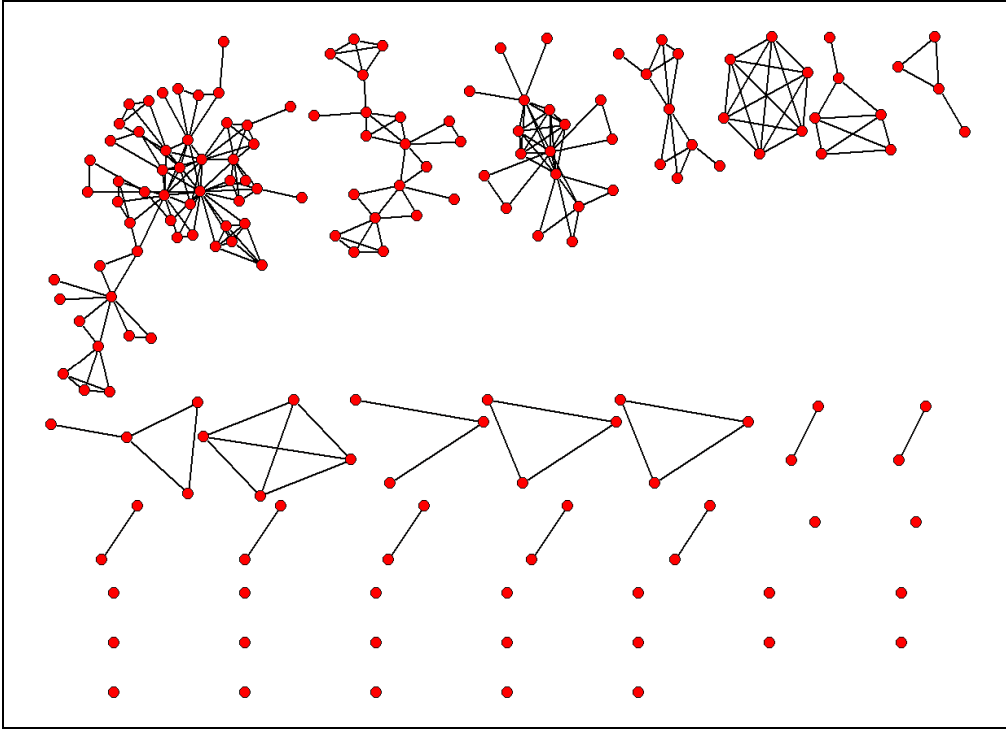


Figure 4.4. Social network in 2007

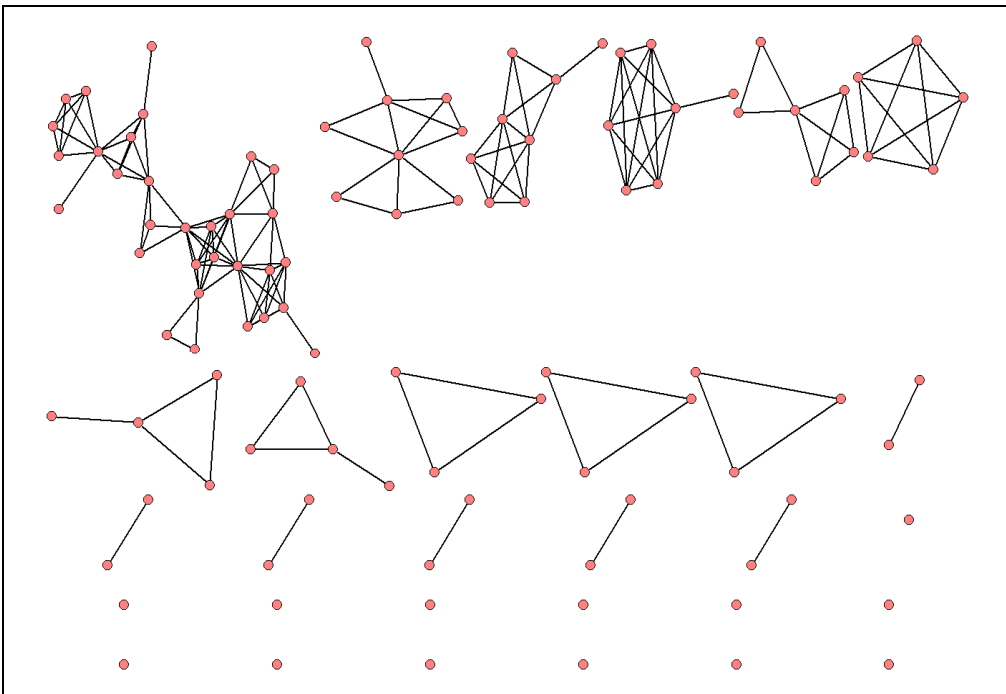


Figure 4.5. Social network in 2008

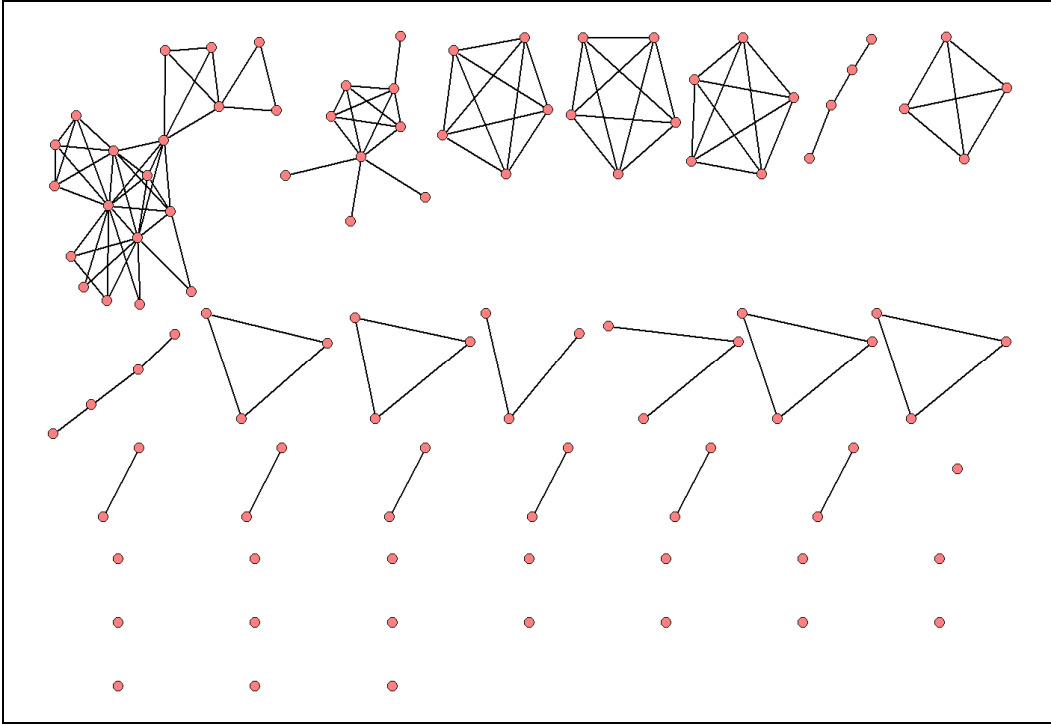


Figure 4.6. Social network in 2009

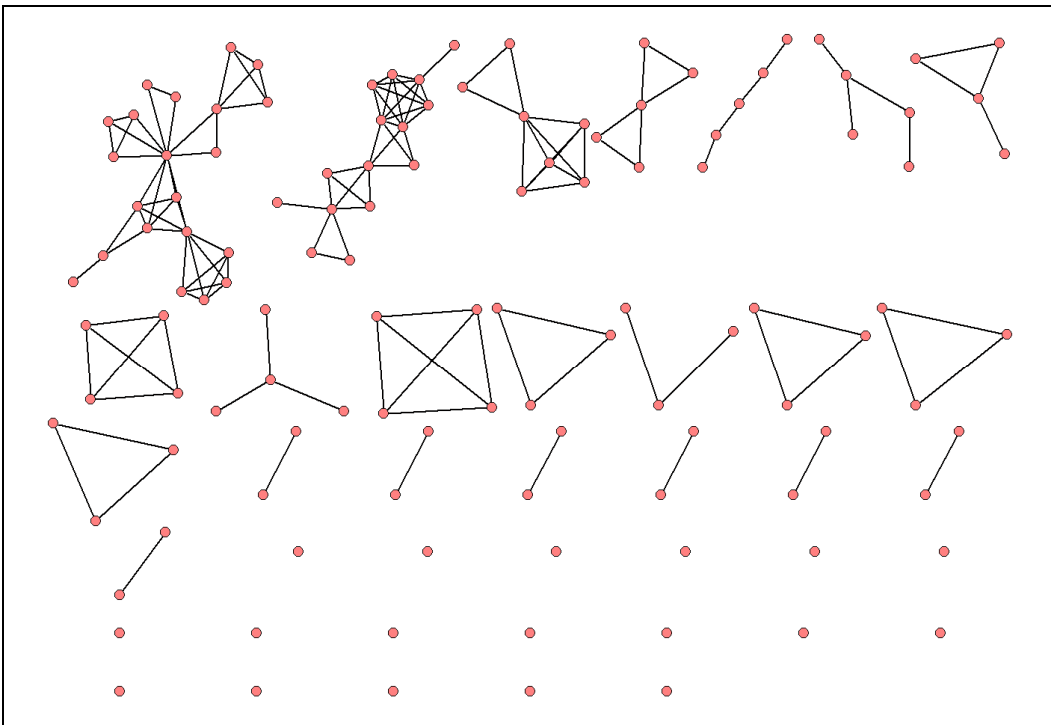
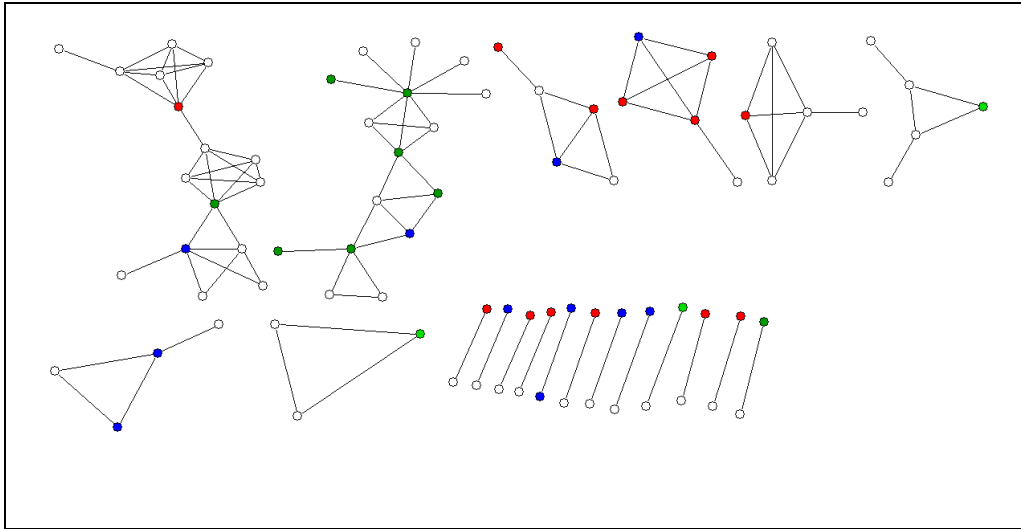


Figure 4.7. Social network in 2010

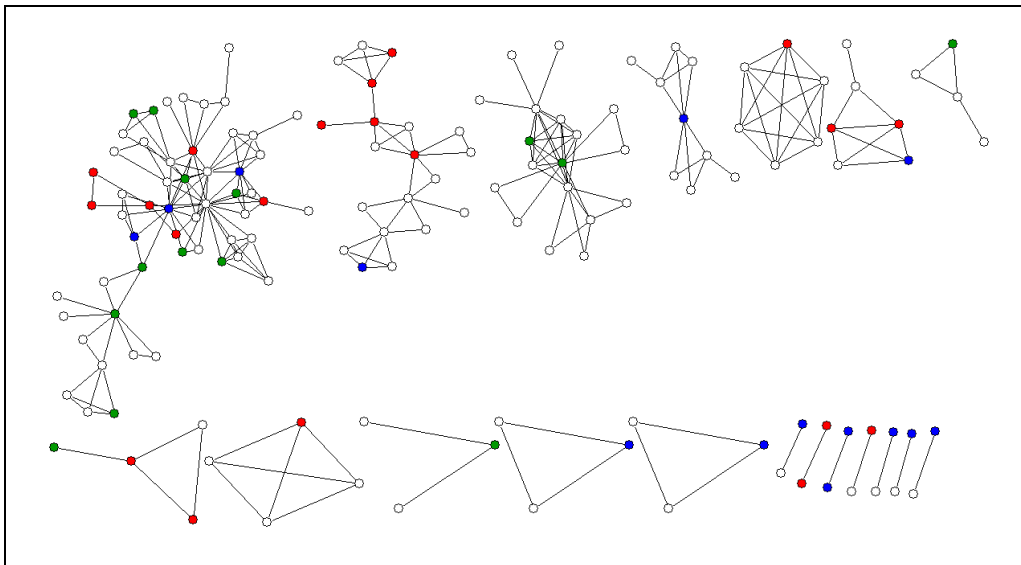
Analysis of the data also revealed a counterintuitive finding. Prior research has largely discussed components (i.e., groups or sub-groups) embedded within different cliques or gangs. (See Appendix B for example from Klein, 1995). Analysis of the data for the present study did not support those findings discussed and hypothesized in prior research. In fact, gang members who were identified as members of different cliques were commonly members of the same component, as shown in Table 4.2. This finding suggests that these cliques were more a hybrid gang than three independent cliques (Starbuck, Howell, & Lindquist, 2001). This finding is illustrated in Figures 4.8 through 4.12 which present the yearly networks and identify the different clique affiliations. The white dots are non-gang members, and the colored dots are gang members. The different colors indicate the different cliques.

The figures show that some groups have multiple colors, indicating that different cliques could be part of a single group. The composition of the groups can be found in Table 4.2. Specifically, the percentage of groups (two or more individuals) that were hybrid gangs (multiple cliques in the same group) ranged from 5% in 2009 to 23.8% in 2006. The number of individuals who were in groups that could be considered hybrid groups ranged from 17.9% of individuals in 2009 to 49.7% in 2007. This finding raises serious questions about how the police identify gangs and the composition of cliques. The implications of this finding will be discussed further in the discussion.



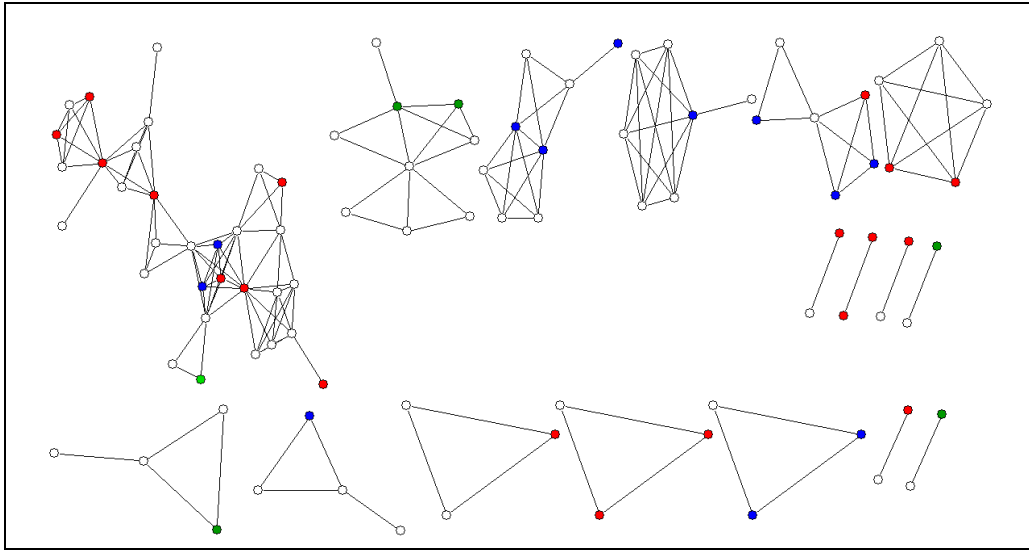
Key: Varrio Sixty First = Red; West Side Grandel = Blue; Varrio Clavalito Park = Green

Figure 4.8. 2006 network with clique affiliations



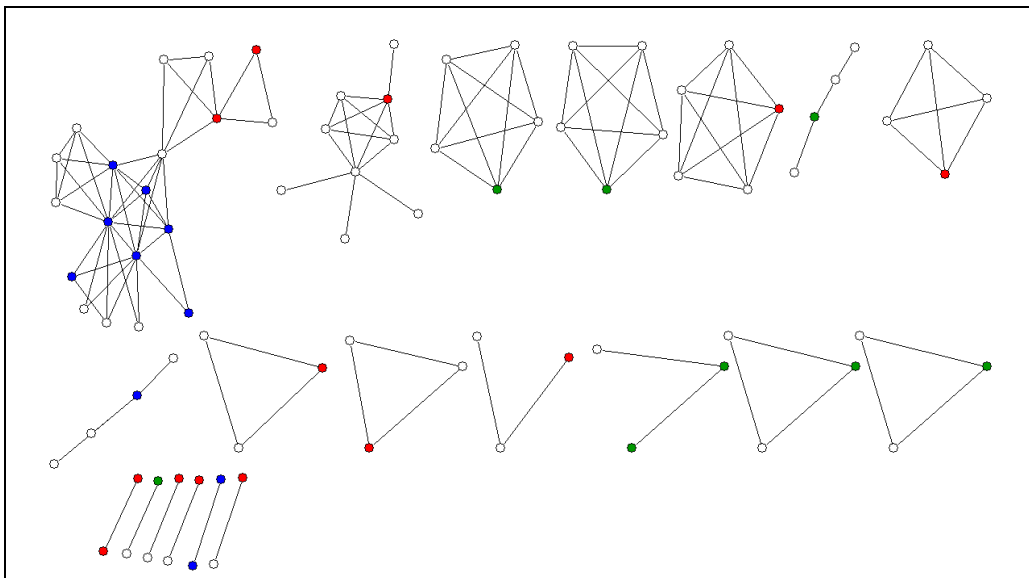
Key: Varrio Sixty First = Red; West Side Grandel = Blue; Varrio Clavalito Park = Green

Figure 4.9. 2007 network with clique affiliations



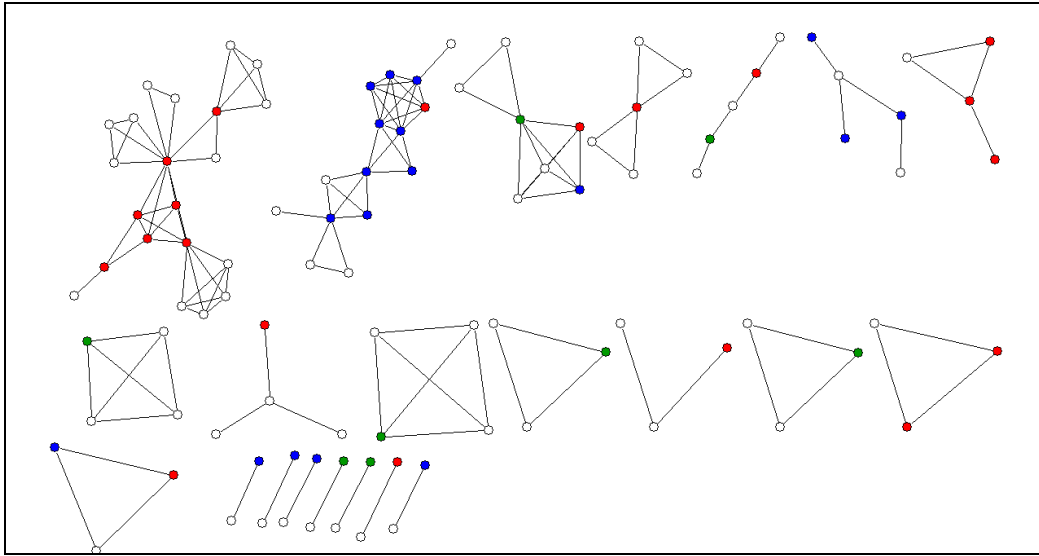
Key: Varrio Sixty First = Red; West Side Grandel = Blue; Varrio Clavalito Park = Green

Figure 4.10. 2008 network with clique affiliations



Key: Varrio Sixty First = Red; West Side Grandel = Blue; Varrio Clavalito Park = Green

Figure 4.11. 2009 network with clique affiliations



Key: Varrio Sixty First = Red; West Side Grandel = Blue; Varrio Clavalito Park = Green

Figure 4.12. 2010 network with clique affiliations

Next, I examined network overlap from year to year -- in other words, whether specific individuals were included in the network from year to year. Table 4.13 displays the hypothetical temporal combinations of potential inclusion in the network, regardless of the actual number of individuals who fit the category in the present study. Since the networks were built by year, it was possible for an individual to be included in any number of the 5 years, in any combination. A shaded square in Table 4.13 indicates inclusion in the network. For example, the first row indicates the percentage of the sample that was included in the network only in 2006. Further, the combinations are partitioned by number of years. The first block shows the five combinations that indicate that a person was in the network only in one year; the second block shows the possible combinations for those in the network for two years, and so on. The final two columns show the percentage of individuals who matched that specific combination and the percentage of individuals who were included in a given number of years. This table shows that almost 80% of those in the study were in the network for only one year (see final column); 15% were included in the network for two years; 4% were included in the network for three out of the 5 years, 1.5% for four years, and no individuals were in the network for all five years of the study. This table shows a high turnover in these networks from year to year. This finding supports previous research that suggests that the majority of gang members are involved in the gang for less than a year (Thornberry et al., 2003).

Table 4.13

All possible yearly combinations of being in the network.

	2006	2007	2008	2009	2010	N	Percent	Total
1 year in the network						59	12.7%	79.4%
						118	25.4%	
						60	12.9%	
						57	12.3%	
						75	16.1%	
2 years in the network						13	2.8%	15.0%
						4	0.9%	
						5	1.1%	
						3	0.6%	
						10	2.2%	
						3	0.6%	
						9	1.9%	
						8	1.7%	
						6	1.3%	
						9	1.9%	
3 years in the network						2	0.4%	4.0%
						1	0.2%	
						0	0.0%	
						2	0.4%	
						2	0.4%	
						0	0.0%	
						1	0.2%	
						1	0.2%	
						4	0.9%	
						6	1.3%	
						1	0.2%	
						0	0.0%	
4 years in the network						1	0.2%	1.5%
						0	0.0%	
						2	0.4%	
						0	0.0%	
						4	0.9%	
5 years						0	0.0%	0.0%
Totals						465	100.0%	100.0%

Summary of Findings

Some important findings about the nature and utility of these data were revealed in this chapter. First, relational data from official police data can in fact be used to construct social networks. Second, rather than yearly networks being one large connected network, they consisted of many disconnected groups. Third, gang members not only were connected to non-gang members, but members from different cliques often were found to be part of the same group. Fourth, the network had high turnover from year to year. These four findings give unique insight into the social structure of street gangs.

The first major finding from this chapter is that social networks can be built from official police data. A number of official police data sources could be converted to relational data sets; these sources are under-utilized. One readily available source of relational data comes from field interview cards. Relations can be established through field interview cards, and analyzable social networks can be created. The usefulness of these data and the implications for their use will be shown in the remaining chapters.

The second major finding from this chapter is that the networks that emerged from year to year were not connected networks, but disconnected groups. Rather than being one large cohesive group, the network consisted of many smaller connected groups. This finding is supported by prior research that has suggested that gangs do not typically hang out together, but instead they socialize in smaller groups of associates (Thrasher, 1927; Decker & Van Winkle, 1996). The differences between having a large connected group and having a number of smaller groups are important. Specifically, with smaller groups it is more likely that information and goods (e.g., drugs, guns) will take longer to disperse throughout the network. This was found across years, as well. That is, the

network looked similar across time, with a few larger connected groups, some smaller groups, and a series of dyads and isolates. Overall, this method of creating networks through FI cards identified a highly criminal network of gang and non-gang members. Even though the social network was not a large connected group, the method consistently identified groups -- some large and some small -- of connected individuals.

The third major finding was that gang members from different cliques were in the same social network. Documented gang members were tied not only to non-gang members (as would be expected), but they were also associated with gang members from other cliques. Official police data identified three unique cliques; however, the social network visualizations showed that members from different cliques often were socially tied to one another. This finding raises questions about the study of gangs and the appropriate unit of analysis for studying gang structure. If gang members from different gangs or cliques routinely associate with each other, the appropriate unit of analysis is the network and not the named gang. Criminal behavior will take place through these groups, and a better understanding of the social structure will be just as important as knowing the characteristic of the named gang or clique. That is, understanding the informal social structure compared to the formal aspects of the structure (e.g., leadership, rules, signs, symbols) will lead to insights about the mechanisms that produce crime.

The fourth major finding from this chapter is that there was high network turnover from year to year. Specifically, about 80% of those in the sample were present in the network for only one of five years. That is, each year the social network was comprised of almost entirely new individuals. This high level of turnover is supported by prior research (Thornberry et al., 2003). High levels of group turnover make structure and

organization more difficult to sustain. This finding will be important to keep in mind as this study examines the group-level social structure of these groups.

CHAPTER 5: NETWORK POSITION AND CRIMINAL BEHAVIOR

Much quantitative gang research has been conducted at the individual level (Esbensen & Osgood, 1997; Esbensen et al., 2001; Decker et al., 2008). As mentioned in chapter 2, while individual-level research has helped researchers and policymakers understand gang organization, its reliance as the unit of analysis has limited our understanding of the relationship between the gang, the individual's position within the gang, and crime. The analysis presented in this chapter complements and expands on this body of research by examining how network centrality and arrest are related. Specifically, this chapter will examine whether individuals most central to the gang are the most likely to be arrested. Further, this chapter will determine which operationalization of centrality is the strongest predictor of arrest within networks of gang members and associates.

This chapter explores these questions by examining the networks by year using four different measures of centrality. A centrality measure is a score given to each individual that is an indication of that individual's importance to the network, based on different operationalizations of centrality (Borgatti & Everett, 2006; Freeman, 1977). The four most common measures of centrality include (a) degree, (b) closeness, (c) betweenness centrality, and (d) eigenvector centrality (Freeman; de Nooy et al., 2011).

Analytic Strategy

Measures of centrality indicate who is most central to the network. Those with higher centrality measures are more likely to possess information (or goods) that flow throughout a network. Although measures of centralization are general measures of the

entire network (i.e., all groups), measures of centrality are the individual elements of the centralization measures. The following section describes the four centrality measures that will be used to identify those individuals most important to the gang. Following these descriptions, I present findings on the four centrality measures and how they are related to individual levels of criminal involvement within the network. Specifically, the analysis will determine which measures are associated with criminal involvement, measured by arrest.

Measures of centrality.

Four measures of centrality were used to identify those who are most central to the network. Generally, those who have easier access to information, or those through whom information must pass in order to be dispersed throughout the network, are considered most central in a network. Centrality, however, can be defined in different ways. The four measures of centrality examined for this chapter were (a) degree centrality, (b) closeness centrality, (c) betweenness centrality, and (d) eigenvector centrality. Each centrality measure was calculated for each node in the network for a given year. Next, a sociogram was created for each measure with the size of the node being relative to the given node's centrality score. This allowed for visualization of the network and illustrated the most central actors in the network. Pajek was used to calculate all the centrality measures, and all centrality scores were normalized so that the scores could be compared across networks of different size.

The first measure of centrality, degree centrality, is the simplest. The degree centrality of a node is simply the degree of that particular node (de Nooy et al., 2011; Wasserman & Faust, 1994). Once again, the degree of a node is equal to the number of

ties a node has in the network. Degree centrality suggests that those who have the most ties are the most central to the network, but they are not necessarily the most strategic actors (Morselli, 2009).

The second measure of centrality is closeness centrality. This measure incorporates the concept of distance. Although there might be many different paths between two nodes in a network, the shortest is the geodesic distance, and each combination of two nodes has a geodesic distance. Closeness centrality takes all the geodesics into account (Wasserman & Faust, 1994). Closeness centrality is calculated as the number of other nodes in the network divided by the sum of the geodesic distances between that node and all other nodes in the network. As a result, if a node was directly connected to all other nodes in the network, its closeness centrality score would be one; as the distances become greater, its score becomes something less than one (de Nooy et al., 2011).

The third measure of centrality is betweenness centrality. This measure of centrality is based on the principle that individuals are more important to a network if they control the flow of information in the network, given their position. Again using the concept of the geodesic, betweenness centrality is calculated as the proportion of all geodesics that include the particular node (de Nooy et al., 2011). That is, the proportion of shortest distance communication chains included in a given node, the more geodesics a node is included in, the more information they potentially control and the more important they are to the network.

The fourth and final measure of centrality used in the present study is eigenvector centrality. Eigenvector centrality denotes that individuals are central to a network to the

extent that they are centrally located, but also to the extent that they are connected to others who are centrally located. Thus, the centrality of one's friends is taken into account by including not just who you know, but also by whom your friends know. If a node is connected to many influential nodes, then he or she is likely to have greater influence over a network. The name comes from the fact that eigenvector centrality is calculated using the first normalized eigenvector in the network's relational matrix (see Wasserman & Faust, 1994).

Centrality and criminal involvement.

After calculating an individual's centrality, the next step is to examine how that measure is related to arrest. In order to assess the relation between network position and criminal behavior, I conducted a series of logistic regression models with the outcome variable of interest being arrests. The main independent variables are the individual's scores of centrality (i.e., degree, closeness, betweenness, and eigenvector). A number of control variables are included in the analysis, as well. All models control for gender, age, and whether or not the person was a documented gang member or Hispanic. A control variable was also created to control for any unique variation caused by individuals who entered the network in more than one year.⁵ Additionally, a control was included for yearly variation. Finally, given the clustered nature of the data (individuals in groups), robust standard errors for clustering were used (Cameron & Trivedi, 2010).

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⁵ Network characteristics for an individual are derived from the person's network in a given year. Since individuals cannot enter the network more than once per year, their network characteristics are unique to their position in a given year. This data structure, and controlling for those who enter more than once over 5 years, will limit the clustering based on the individual.

Findings

I first present findings on the relation between network centrality and criminal behavior. I examine whether those who are most central to the network are more likely to be involved in criminal behavior. All four centrality measures compare those at the top third of the distribution with those in the bottom two-thirds of the network (Farrington & Loeber, 2000; Katz & Fox, 2010). Criminal behavior is measured by whether or not an individual was arrested in a given year.

Table 5.1 displays the relationship between the four measures of centrality and being arrested. Model 1 estimates the effect of degree centrality. Those who were high in degree centrality were not significantly more likely to be arrested than those who were not. The only variable that significantly increased the odds of being arrested was whether or not the person was a gang member: The odds of being arrested were 81% higher for gang members than for non-gang members. Model 2 displays the relation between those with high betweenness centrality and being arrested. Betweenness centrality was the only centrality measure significantly related to arrest. Being high in betweenness centrality increased the odds of being arrested by 161%. As a reminder, betweenness centrality is based on the idea that the more individuals who have to go through you to get to others in the network, the higher your betweenness centrality. Additionally, being a gang member increased the odds of arrest by about 77% over those of being a non-gang member. Model 3 displays the relation between closeness centrality and arrest, net of controls. Those high in closeness centrality were no more likely to be arrested than those with low closeness centrality. Again, being a gang member was significantly related to an increase

in the odds of arrest. The final model in Table 5.1 displays the relation between eigenvector centrality and arrest. Those with high eigenvector centrality were not significantly more likely to be arrested. Controlling for eigenvector centrality, gang members had an 80% higher odds of arrest than non-gang members. Overall, Table 5.1 shows that at the individual level, the only measure of centrality that increased the odds of arrest was betweenness centrality. Further, gang membership was related to an increase in the odds of arrest across all four models.

Prior literature has found that gang membership increases criminal behavior because it increases criminal embeddedness (Bernburg, Krohn, & Rivera, 2006). Given the importance of being a gang member, it might be that it is not just being central to the network or just being a gang member that increases the likelihood of criminal behavior. Rather, it may be that being *both* a gang member and a central person in the network is the factor that would increase one's likelihood of being involved in crime. This interaction will be further examined next.

Table 5.2 displays the results of regression models examining the interaction between gang membership and centrality. Given the dichotomous nature of the variable, a categorical variable was constructed. Each person was categorized as (a) Non-gang member/ Low centrality, (b) Gang member/ Low centrality, (c) Non-gang member/ High centrality, or (d) Gang member/ High centrality. Model 1 in Table 5.2 shows the interaction of gang membership and degree centrality on arrest. Similar to the findings in Table 3.1, gang members were significantly more likely to be arrested; gang members with low degree centrality had an 82.9% higher likelihood of arrests than non-gang members with low degree centrality; gang members with high centrality had a 135%

higher likelihood of arrest. Degree centrality increased the odds of arrest for gang members by about 28.5%.

Model 2 in Table 5.2 shows the results of the interaction between gang membership and betweenness centrality on arrest. Gang members with low centrality, when compared with non-gang members with low betweenness centrality (the reference group), had significantly higher odds of arrest (92%). When compared with the reference group, gang members and non-gang members with high betweenness centrality each had significantly higher odds of arrest (295% and 231%, respectively). Interestingly, gang members with high betweenness centrality had 105% higher odds of arrest than gang members with low betweenness centrality.

Model 3 in Table 5.2 displays the results of the interaction of gang membership and closeness centrality on arrest. Gang membership was related to an increase in arrest despite the level of closeness centrality. There was evidence that closeness centrality enhanced the effect, however. Gang members with low closeness centrality and those with high closeness centrality had significantly higher odds of arrest than the reference group. Among gang members, those with high closeness centrality had 30.5% higher odds of arrest than gang members with low centrality.

Model 4 in Table 5.2 shows the interaction effect of gang membership and eigenvector centrality and arrest. Following the pattern of the previous models, gang members had significantly higher odds of arrest regardless of their level of centrality, when compared with non-gang members with low centrality. Gang members with high eigenvector centrality, however, had 60.6% higher odds of arrest than gang members with low eigenvector centrality.

Summary of findings

Three major findings about gang social networks and crime emerged from this chapter. First, prior literature indicated that betweenness centrality is an important network position for understanding criminal networks (Morselli, 2009), and this finding was confirmed by the current analysis. The only centrality measure independently related to arrest was betweenness centrality. Individuals with high betweenness centrality occupied a position in the network that allowed them to be connected to different groups and potentially to different types of information and opportunities. The second finding is that documented gang members were more likely to be arrested than non-gang members. This finding is consistent with the prior literature (Katz et al., 2000).

Finally, I found that network centrality can enhance the likelihood of arrest for gang members. For one measure of centrality, betweenness, the enhancement occurred for both gang and non-gang members. Although three of the centrality measures did not have independent effects, there is evidence that centrality contributed to the criminality of gang members. Gang members who were high in degree centrality had about 28% higher odds of being arrested than gang members who did not have high degree centrality. Gang members with high betweenness centrality had about 105% higher odds of arrest than other gang members; this effect was about 30% for closeness centrality and about 60% for eigenvector centrality. For all four measures of centrality, being more central to the network increased a gang member's likelihood for arrest. In other words, it was not just being a gang member, but being a gang member and holding an important network position that increased one's likelihood of arrest. For non-gang members, only those who

were high in betweenness centrality were more likely than the reference group to be arrested. This interaction between gang membership and betweenness centrality tells us that an individual's position in the network matters. That is, those who are high in betweenness centrality, gang member or not, are more likely to be criminally involved.

The evidence suggests that there is a hierarchy in terms of criminal involvement. At the bottom are those who are not gang members and have low betweenness centrality, followed by gang members with low betweenness centrality, followed by non-gang members with high betweenness centrality, and at the top are those who are gang members and have high betweenness centrality. This finding has a number of implications, both theoretically and practically, which will be presented in the discussion section.

Table 5.1

Logistic regression, effect of centrality on being arrested

Dependent Variable	Arrested		Arrested		Arrested		Arrested	
	OR	SE ^a	OR	SE	OR	SE	OR	SE
High Degree Centrality	1.307	(0.281)						
High Betweenness Centrality			2.618	** (0.724)				
High Closeness Centrality					1.196	(0.247)		
High Eigenvector Centrality							1.323	(0.261)
Gang Member	1.810	*	1.769	**	1.804	**	1.805	**
Hispanic	1.517	(0.340)	1.443	(0.327)	1.489	(0.338)	1.507	(0.339)
Female	1.356	(0.400)	1.359	(0.397)	1.340	(0.398)	1.352	(0.398)
Age	1.000	(0.009)	1.002	(0.010)	1.000	(0.009)	1.000	(0.009)
Multiple years in network	1.084	(0.205)	0.989	(0.186)	1.094	(0.205)	1.082	(0.203)
Year (2006 reference)								
2007	0.815	(0.203)	0.777	(0.183)	0.808	(0.198)	0.819	(0.204)
2008	0.658	(0.178)	0.688	(0.176)	0.658	(0.174)	0.660	(0.176)
2009	0.900	(0.237)	1.042	(0.265)	0.914	(0.238)	0.898	(0.234)
2010	0.891	(0.285)	0.988	(0.306)	0.937	(0.295)	0.921	(0.286)
N	594		594		594		594	
Wald Chi-Square (df)	27.23**(10)		34.72**(10)		27.74**(10)		29.71**(10)	
Nagelkerke r-squared	0.057		0.091		0.054		0.057	

* p<.05; **p<.01

^a All standard errors are robust standard errors for clustering on component

Table 5.2

Logistic regression, effect of interaction of centrality and gang membership on being arrested

Dependent Variable	Arrested		Arrested		Arrested		Arrested	
	OR	SE ^a	OR	SE	OR	SE	OR	SE
Centrality Measure								
Non-Gang/ Low Centrality		reference category		reference category		reference category		Eigenvector reference category
Gang/ Low Centrality	1.829 *	(0.476)	1.921 **	(0.410)	1.720 *	(0.442)	1.613 *	(0.385)
Non-Gang/ High Centrality	1.324	(0.362)	3.315 **	(1.063)	1.124	(0.285)	1.142	(0.293)
Gang/ High Centrality	2.350 *	(0.779)	3.950 **	(1.717)	2.245 *	(0.785)	2.591 **	(0.844)
Hispanic	1.516	(0.341)	1.427	(0.325)	1.495	(0.340)	1.522	(0.344)
Female	1.358	(0.393)	1.382	(0.410)	1.329	(0.391)	1.322	(0.388)
Age	1.000	(0.009)	1.001	(0.010)	1.000	(0.009)	1.001	(0.009)
Multiple years in network	1.084	(0.205)	0.994	(0.187)	1.093	(0.205)	1.077	(0.202)
Year (2006 reference)								
2007	0.815	(0.203)	0.772	(0.182)	0.811	(0.198)	0.826	(0.202)
2008	0.658	(0.177)	0.673	(0.174)	0.660	(0.173)	0.665	(0.174)
2009	0.898	(0.237)	1.047	(0.268)	0.923	(0.238)	0.921	(0.235)
2010	0.890	(0.286)	0.999	(0.309)	0.942	(0.297)	0.925	(0.283)
N	594		594		594		594	
Wald Chi-Square (df)	24.50**(11)		43.36**(11)		24.77**(11)		29.54**(11)	
Nagelkerke r-squared	0.057		0.093		0.054		0.059	

* p<.05; **p<.01

^a All standard errors are robust standard errors for clustering on component

CHAPTER 6: GANG SOCIAL STRUCTURE

Much of our quantitative understanding of gang organization has come from individual-level analysis (Decker et al., 2008; Bouchard & Spindler, 2010; Pyrooz et al., 2011; Esbensen et al., 2001; Bjerregaard, 2002) and surveys of law enforcement agencies (Klein & Maxson, 2006). The prior research on gang organization has led to some important understandings about the characteristics of gangs and their organization, but there is still a gap in the literature that is largely associated with unit of analysis. More than 20 years ago, Short (1988) called for more group level analysis of gangs, but this body of research has been slow to develop. The current study expands on prior research by focusing on the group as the unit of analysis.

Analytic Strategy

I used three analytical steps to examine gang social structure and its relationship to crime. The first step was to examine the levels of density and centralization of the networks by year. The second step was to use Zero-One (ZO) analysis to measure level of transitivity (in the case of undirected networks, this is a triangle) by year. Finally, I used regression analysis to examine how density and centralization are related to criminal behavior, controlling for other important group level factors. In sum, this chapter will explore density and centralization at the group level, the role of transitive triads, and the relations between group level characteristics and the group rate of offending. The rationale for the analytical process used in this chapter is outlined further below.

Network density and centralization.

The chapter will begin by examining overall network structure. A number of different indices have been developed to measure the level of cohesion and the level of centralization in a network. Density is the most commonly used measure of cohesion. A density measure is the proportion of ties that exist over the total number of ties that could potentially exist (Wasserman & Faust, 1994; de Nooy et al., 2011). If everyone in the network was tied to everyone else in the network, the density of that network would be 1; if no one was connected to anyone else, the density would be 0. Thus, the closer the density measure is to 1, the more dense and cohesive the network.

The next step in describing the network is to examine its level of centralization. Centralization measures the flow of information throughout the network. High levels of network centralization indicate role differentiation in the network (i.e., not all in the network are equal). The more roles there are in the network, the more some individuals will be advantaged in terms of access to information (or whatever else the network has to offer). Centralization refers to the entire network, while centrality refers to a specific node in the network. As in the previous chapter, the four measures of centralization that I have used in the present study are degree centralization, closeness centralization, betweenness centralization, and eigenvector centralization.

First, degree centralization is a measure ranging from 0 to 1, with 1 indicating the most centralized network. The degree of a node is the number of ties it has to other nodes in the network. Thus, degree centralization is calculated as the variation in degree among nodes divided by the maximum possible variation in a network of the same size (de Nooy et al., 2011; Wasserman & Faust, 1994). The more variation in degree there is in a

network, the more centralized that network is. This might seem counterintuitive at first, but if everyone had equal access to all other individuals in a network, then the network would inherently not be centralized; instead, everyone would have equal access to information. For this reason, more diversity in positions and degree will mean more overall network centralization generally (de Nooy et al., 2011).

Second, closeness centralization measures social distance through geodesics. A geodesic is the shortest path between two nodes in a network, and the length of a geodesic is referred to as the distance between the two nodes. Closeness centralization is calculated as the variation in the average distances (using the geodesics) of nodes divided by the maximum possible variation in closeness scores.

The third measure of centralization is betweenness centralization. Betweenness can best be understood in terms of the flow of information. If information were to flow through a network, as it often does, who are the people that information would have to flow through most frequently, and who are the individuals through whom information does not flow? As with the previous centralization indices, the betweenness centralization measure is calculated as the variation in betweenness centrality measures (the individual-level measure of betweenness) divided by the maximum possible variation in betweenness centrality in a network of the same size. Again, higher variation is an indication that the network is more centralized, that information must flow in distinct ways and not through random avenues. The final centralization measure to be presented is eigenvector centralization. Eigenvector centralization adds the weight of who your associates know. Thus, it is not just who you know, but how connected your friends are to others in the network. Eigenvector centralization is calculated as the variation in

eigenvector centrality (individual measure of eigenvector centralization) divided by the maximum possible variation in eigenvector centrality (de Nooy et al., 2011).

In sum, one measure of density and four measures of centralization will be used to assess the social organization of the different components and to evaluate how the social structure changed or stayed the same over the 5-year period. Each measure of centralization taps into a different, but related, aspect of how centralized the network is and the amount of differentiation in roles in the overall network. These measures provide useful information about the social structure of groups over time. Specifically, these measures show the amount of cohesion and role differentiation present in gang social networks.

Levels of transitivity.

Density and centralization refer to the entire network. The triad (the relationship between three individuals) is a building block of network structure; the transitive triad is of particular importance. Transitivity is the concept that a friend of a friend will become a friend (Wasserman & Faust, 1994). As transitivity increases over time (referred to as triadic closure), it is an indication that the network is becoming more cohesive. In the current study, we are using undirected relationships, thus a transitive triad would be manifested as a triangle (Pajek sequence code 16-300). As individuals introduce their friends to other friends, we would expect the number of transitive triads to increase. Transitivity is important in that it is a direct measure of cohesion and closeness within a network.

The Zero–One package in StOCNET will be used to determine the probability distribution of network statistics and to assess the level of transitivity in a network. ZO

calculates the distribution for undirected graphs based on the degree and size of the original network. By controlling for the size of the network and the number of ties in the network, one can test whether a structural property (transitivity in this case) is significantly more likely to occur in the observed network than in a large number of random networks of the same size. The simulated networks provide the null hypotheses for testing the level of transitivity in the observed network. It is appropriate to control for degree and mutuality since transitivity is of higher order (Snijders, 2002); because the current study has only undirected ties, mutuality is not an issue.

The measure of transitivity used in ZO is a ratio of the number of transitive triplets divided by the number of transitive triads, plus the number of intransitive triads, multiplied by 100. This measure can be interpreted as the percentage of triads that are transitive. This ratio is preferable because all networks fall between 0 and 100. To determine if there is significantly more transitivity than randomness, a z-score is calculated.⁶ The mean and standard deviation are obtained through simulation of a large number of networks with the same number of nodes and ties. This ratio of transitivity will allow us to examine whether the gang network becomes more cohesive over time, compare different gang networks to each other, and test whether the level of transitivity is significantly different than would be produced by a random process.

Relation to criminal behavior.

In order to assess the relation between group characteristics and criminal behavior, a series of ordinary least squares regression models were conducted. The unit

⁶ A maximum z-score of 3.72 was set given the distribution was drawn from 10,000 simulated networks. For all five years in Table 6.1 the z-score for the observed network, calculated from the mean and standard deviation of the simulated networks of a similar size, would be substantially greater than 3.72, however, a z-score of 3.72 leaves 1/10,000 in the upper tail of the distribution.

of analysis is the group. The outcome in these models is arrest, specifically, the percentage of group members who were arrested. The primary independent variables are the group density and centralization measures (i.e., degree, closeness, betweenness, and eigenvector). The control variables are average age, gender composition, percentage of documented gang members, year of the data, group density, size of the component, percentage of transitive triads, and whether or not the group is a hybrid (more than one gang clique represented in the group). Given the exploratory nature of this analysis and the few units of analysis ($n=60$), the control variables were assessed one at a time to determine which would be included in the full models. Robust standard errors were used to correct for any heteroskedasticity (Cameron & Trivedi, 2010).

Findings

Table 6.1 shows the number of individuals and the number of ties. Next, the transitive ratio is shown. The transitive ratio indicates the percentage of triads that are transitive. A transitive triad in a non-directed network looks like a triangle, that is, three individuals who all know each other. The first section of Table 6.1 shows the observed statistics for each year. The transitive ratio is greater than 50 across all 5 years: 59 in 2006, 51 in 2007, 70 in 2008, 66 in 2009, and 65 in 2010. The transitive ratio can be interpreted as the percentage of triads that are transitive -- that is, the percentage of three-person relationships in which all three people are connected to each other.

The next section of Table 6.1 shows summary results of the simulated networks. For each year, 10,000 networks were simulated. Each simulated network had the same number of individuals and the same number of ties as the observed yearly network. Ties were randomly distributed in the simulated networks. The simulated networks create a

sampling distribution given a network with the number of individuals and ties for each year. The mean transitive ratio of the simulated networks in 2006 was 2.76, compared with 3.72 in 2007, 4.73 in 2008, 4.34 in 2009, and 3.02 in 2010. These results show that in the simulated networks, the percentage of transitive triads ranged anywhere from 2% to 5%. This indicates that the networks of the same size with the same number of ties tended to have a much lower level of transitivity. When networks were randomly created, the level of cohesion in those random networks, when compared to the observed networks, was low. With the random sample of simulated networks, a z-score can be calculated using the observed network. Across all 5 years, the observed networks had a significantly higher transitive ratio than the mean of the simulated networks. These results indicated that the observed networks did in fact tap into social processes far beyond those of a sample of randomly generated networks with the same number of individuals and ties.

Transitivity is a measure of social process. As is shown, randomly generated networks have low levels of transitivity because they are not representing social activity, but just randomness. Networks that are measuring social process will move toward triadic closure, that is, friends of friends will become friends. This process of triadic closure is measured through transitivity. Thus, the gang social networks have significantly more transitivity than would be expected if the network was randomly generated.

Table 6.1.

Level of transitivity by year using Zero-One (ZO)

	2006	2007	2008	2009	2010
Observed number of individuals	94	169	108	103	121
Observed number of ties	96	250	165	122	140
Observed Transitive Ratio	59	51	70	66	65
<u>Transitivity of simulated networks</u>					
Estimated mean transitive ratio	2.76	3.72	4.73	4.34	3.02
Estimated variance	3.58	1.15	2.13	3.05	2.02
Estimated SD	1.89	1.07	1.46	1.75	1.42
z-score	3.72	3.72	3.72	3.72	3.72
p-value	0.00	0.00	0.00	0.00	0.00

^a For each year the network was simulated 10,000 times. Each simulated network had the same number of individuals and ties as the observed network

The second approach to understanding group-level social structure will be to examine the levels of density and centralization at the group level. (A group here is defined as three or more connected individuals.) As a reminder, Figures 1.5 through 1.9 show the networks by year. For this analysis, the unit of analysis is components within year. There were 8 groups in 2006, 12 in 2007, 11 in 2008, 14 in 2009, and 15 in 2010. Density is an indicator of social cohesion that measures the proportion of ties that do exist in the group, considering the possible number of ties that *could* exist. Centralization measures indicate the amount of role differentiation as defined by the type of centralization. Table 6.2 displays the average levels of density and centralization across years (average of the groups in that year).

Prior to presenting the findings, two issues should be further clarified. First, the unit of analysis is the group (or component). The density and centralization levels were not calculated for the entire year, but instead were calculated for each connected group within year. Second, only those groups that had three or more individuals were included in the analysis, because density and centralization measures are constants and do not provide much meaning with groups of two (dyads) or single individuals (isolates). For example, there is only one tie in a group of two, so there cannot be any variation in density. Therefore, the sample was restricted to those individuals who associated with three or more individuals. The findings presented are the mean values for groups of three or more.

As shown in Table 6.2, density was lowest in 2006 at 0.57, then increased to 0.62 in 2007, 0.71 in 2008, and peaked at 0.78 in 2009; it then dropped slightly to 0.69 in

2010. Thus, on average about 60% to 75% of all possible ties existed within groups. Remember that these are average group-level measures for each year. That is, since there were numerous groups within each yearly network, the measures are reported as the average of the groups within a given year. Given this, the average density is the proportion of ties an individual has with those in the group, not the proportion of ties that potentially one could have in the entire network. The analysis indicates a high level of density that is consistent across years.

Next, the centralization measures are presented in Table 6.2. As centralization increases, this is an indication of more variation in the given type of centrality. A score of 1 on centralization indicates the maximum amount of variation in the measure, and a centralization score of 0 indicates that all members in the group occupied the same position, as defined by the type of centrality.⁷ The four types of centralization average from 0.3 to 0.5, which suggests little role differentiation within groups. The one measure that stands out in Table 6.2 is eigenvector centralization in 2009 and 2010. Although not significant, these descriptives suggest that there was more clustering in parts of groups in those years. That is, there were some cohesive sub-groups within groups in 2009 and 2010.

Overall, the findings indicate generally high levels of density and low levels of centralization across years. This suggests that the groups are cohesive and that there is little variation in position within the group. This is to be expected; as cohesion increases (as measured by density), each individual has access to more individuals in the network,

⁷ The author is not aware of any standard cut-points for interpreting these measures. Given this, the measures are standardized and range from 0 to 1. Thus, one could divide them in thirds and interpret them as low, moderate, and high. This interpretation suggests that density is moderate to high, and the centralization measures are generally low to moderate.

which reduces the number of positions in the group. If everyone in a group was connected to everyone else, there would be maximum density (and cohesion) and everyone would have the same position in the group (access to the same information), leaving centralization at 0.

Table 6.2.

Average levels of density and centralization

Groups with three or more	2006		2007		2008		2009		2010	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Density	0.57	(0.27)	0.62	(0.34)	0.71	(0.28)	0.78	(0.28)	0.69	(0.29)
Degree centralization	0.36	(0.21)	0.34	(0.33)	0.32	(0.29)	0.32	(0.42)	0.35	(0.37)
Closeness centralization	0.41	(0.23)	0.39	(0.34)	0.39	(0.33)	0.32	(0.42)	0.41	(0.39)
Betweenness centralization	0.42	(0.19)	0.38	(0.33)	0.31	(0.28)	0.32	(0.42)	0.41	(0.38)
Eigenvector centralization	0.38	(0.18)	0.47	(0.54)	0.30	(0.27)	0.53	(0.80)	0.53	(0.66)
N	8		12		11		14		15	

* $p < .05$

Group structure and criminal behavior

The final analysis at the group level is to estimate whether variations in density and centralization are related to criminal behavior as measured by arrest. In the current section, the outcome variable is the percentage of group members who were arrested within the year of the network. The unit of analysis is the connected group (the component). Centralization measures are used to indicate the variation in positions within a network. For these measures to have meaning, there must be the possibility that the group could be organized in different ways (de Nooy et al., 2011). When there are fewer than three people in a group (two or one), there is no possibility of variation in that group's social structure. Given the lack of meaning and variation of density and centralization for groups with fewer than three individuals, this analysis includes only groups with three or more individuals, across all 5 years ($n = 60$). The outcome variable is normally distributed, allowing for OLS regression to be conducted; additionally, all standard errors are robust standard errors (Cameron & Trivedi, 2010).

This analysis is exploratory in nature. No prior research examines the relation between density/centralization and the rate of arrest for a group. Additionally, given the small n , which translates to low power, only the significant control variables are included in the models.⁸ The main focus of this analysis is whether group-level social structure impacts the rate of criminal behavior, measured through arrest.

⁸ A post-hoc power analysis was conducted for the regression models that are presented. Given an N of 60, 3 parameters and an alpha of .05, there is a 98.4% chance of detecting a large effect, a 74.7% chance of a medium-sized effect, and a 14.5% chance of a small effect (Erdfelder, Faul, & Buchner, 1996). Small, medium, and large effects were defined as effects .02, .15, and .35, as outlined by Cohen (1988). Thus, the final models have sufficient power to detect medium and large effects.

Table 6.3 estimates the relations between group level characteristics and the percentage of group members arrested. Five control variables were examined: the percentages of group members who were Hispanic, who were female, and who were documented gang members; the average age of group members; and whether or not the group was a hybrid component (more than one clique represented in the connected group). The table shows that the percentages of the group members that were Hispanic, female, or gang members were not significantly related to arrest, and that the model accounted for less than one percent of the variation in the outcome. The average age of group members, however, was related to arrest. For every one-year increase in the group members' average age, there was approximately a one percent increase in the percentage of group members arrested. Average age accounted for about 8% of the variation in the outcome. The final control variable, hybrid group, had a p-value of .06; the effect is substantively meaningful, however. At the group level, hybrid components had about an 11% higher rate of arrest than non-hybrid components. As a result, the final models will control for the average age of the group members as well as for whether or not the group was a hybrid.

Table 6.4 displays the regression models showing the effect of density and the four measures of centralization on the percentage of group members arrested. In each model, we controlled for the average age of group members and whether the group was a hybrid. Across models, the average age of the group members and the indicator of being a hybrid component hold as significant positive predictors of the percentage of group members who were arrested. The effect of a one year increase in the average age of the group members resulted in an increase in the percentage of group members who were

arrested, ranging from 1.22% to 1.39%. The effect of being a hybrid group increased the percentage of group members arrested by a range of 15.62% to 18.15%. Density, degree centralization, closeness centralization, betweenness centralization, and eigenvector centralization all were unrelated to the percentage of members who were arrested. This finding was further replicated using alternative specifications of the outcome variable, including average number of arrests. Despite the alternative specifications, with the data in the current study, a relation between group-level social structure and arrest could not be established.

Summary of Findings

In this section, a number of different methods were used to better understand the social structure of network components. The major finding about group-level social structure from this study was that the gang networks were fragmented (not one large cohesive group), but had consistent levels of cohesion within those fragments (groups or components). Further, the gang social networks were significantly more cohesive (measured through transitivity) than would be expected if the network was randomly generated. Finally, there was no evidence that group-level network measures were related to the probability of arrest.

The analysis did indicate, however, that groups with older members and hybrid groups (different cliques in the same group) corresponded to a higher percentage of group members being arrested. The relations between group-level network measures and arrest could not be established in the current analysis, despite sufficient power to detect a large effect (power = 0.984) and reasonable power to detect a medium effect (power = 0.747).

The possibility remains that a small effect went undetected in the current analysis, however. The theoretical and policy implications of these findings will be outlined in the final chapter.

Table 6. 3:

Regression of arrest on group-level control variables

	% of group members arrested					
	b	SE	b	SE	b	SE
%Hispanic	0.10	(16.23)				
%Female			28.38	(22.77)		
%Gang Members			11.93	(16.43)		
Average Age					1.07*	(0.42)
Hybrid group					11.19 ^a	(5.89)
Constant	54.53*	(13.45)	51.18*	(3.83)	50.22*	(6.76)
					28.70*	(10.84)
					51.82*	(3.91)
N	60		60		60	
F	0.00		0.53		6.47*	
					3.61*	
R-square	0.000		0.007		0.080	
					0.040	

* p< .05

^a p = .06

Note: Standard errors are robust standard errors.

Table 6.4.
Regression of arrest on group-level measures

	Percent of group members arrested					
	b	SE	b	SE	b	SE
Density	6.47	(10.57)				
Degree Centralization			-1.81	(9.61)		
Closeness Centralization					.3.25	(9.34)
Betweenness Centralization						
Eigenvector Centralization					-3.75	(9.75)
Average Age	1.36*	(0.45)	1.36*	(0.45)	1.38*	(0.45)
Hybrid Group	18.15*	(7.14)	15.99*	(6.17)	16.30*	(6.22)
Constant	12.68	(13.94)	18.41	(12.26)	18.30	(12.35)
					18.19	(12.29)
					19.76	(12.17)
N	60		60		60	
F	3.84*		3.80*		3.94*	
R-square	0.160		0.157		0.158	

* p< .05

Note: Standard errors are robust standard errors.

CHAPTER 7: DISCUSSION AND CONCLUSIONS

The goal of this dissertation has been to examine the variation in gang social structure and to assess how those variations are related to criminal behavior measured through arrest. Specifically, the current study created gang social networks from official police data to examine both the individual positions and group-level structures that are related to criminal behavior. Three research questions were examined in this study:

1. Can the relational data gathered from the police be used to examine social networks?
2. Are individuals most central to a social network those who are most criminally active and, related, what network positions most accurately identify the most criminally involved individuals?
3. What are the network structures that differentiate gangs, and are these structures related to group-level crime?

These research questions were answered by examining official police data from 2006 to 2010. Field interview (FI) cards were used to construct social networks of gangs and their associates. If two individuals were identified on the same FI contact, it was determined that the two were related. Two-step networks were created for each of the 5 years of data. The two-step process ensured that all those who were at least two relationships away from a gang member (i.e., a friend of a friend of a gang member) were included in the network. Additionally, an indicator of behavior, a set of arrest records, was collected for each person included in the yearly networks.

The networks created through FI cards and the arrest records were analyzed to better understand how social networks, at the individual and group levels, are important

for understanding the dynamics of criminal and gang behavior. Gang research to date has been limited by its lack of group-level data (Klein, 2005). The current study provides insight into gang social structures using relational data collected by the police. Before discussing the findings and their implications, I will review the study's limitations.

Limitations

A number of limitations should be considered before reviewing the study's findings and discussing their implications. First, the starting point for the networks was the police department's gang list. Second, this study was conducted in one city and cannot be generalized to gangs in other cities. Third, the measure of criminal behavior was arrest, which is an imperfect measure of criminal behavior. Finally, relations were established through the use of field interview cards. These four limitations are discussed below.

The first limitation is that the starting point for building the network was the police department's gang list. Research on the validity of police-generated gang data has been mixed, but some of the most recent research has indicated that gang lists accurately discriminate between those who are of greater threat to a community and those who are not (Katz et al., 2000). Much of the published research that has examined police-generated gang classifications has been single-city accounts, which do not allow for comparisons or generalizability (Chesney-Lind, Rockwell, Marker, & Reyes, 1994; Zatz, 1987; McCorkle & Miethe, 1998; Katz et al., 2000). However, despite the obstacles that police agencies face in collecting gang data, police data are widely available and agencies continue to collect the information. A recent national-level examination of the National Youth Gang Survey data found that police gang data collected nationally were reliable,

with gang and gang member data being stronger than gang homicide data (Katz et al., 2012). There are undoubtedly still issues with gang lists; specifically, individuals can be kept on a gang list for up to 5 years without additional police contact.

The current study overcomes this limitation by examining the gang list in conjunction with FI cards. If a person appeared on the gang list, but had not had police contact in a given year, he or she would show up as an isolate. Gang membership was the starting point for the current study. By including all those who were within two steps of a documented gang member, the selection bias associated with selecting only documented gang members is lessened. By acknowledging the challenges to police-driven gang data, researchers can be aware of their limitations and begin to think of ways to improve data quality.

The second limitation is that the current study was geographically limited to one city. The findings cannot be generalized to other cities or other gangs. I examined the three local street gang cliques that were comprised of mostly Hispanics. Even though these findings cannot be generalized to all street gangs, they should be informative to others interested in conducting similar research, particularly those interested in Hispanic street gangs in the Southwest of the United States. The current study's methodology can be replicated in other communities, and the resulting networks can be compared. The current study offers a systematic method of constructing gang social networks that is easily replicable. Other cities might have very different social structures; determining how and why these structures differ will be important for researchers and practitioners alike.

The third limitation to the present study is that criminal behavior was measured through arrest. A number of concerns are associated with police data generally, and those apply to the current study (Mosher, Miethe, & Phillips, 2002; Katz et al., 2000). The police are not notified of every crime that is committed (Mosher et al., 2002, and they are not able to arrest every person who commits a crime. Many illegal behaviors go undetected by the police and residents, and as a result, a portion of criminal behavior is not recorded. That being said, the more criminal behavior an individual engages in, the more likely he or she is to be arrested. Prior research suggests that self-reported delinquency has predictive validity in relation to official delinquency records; however, more research is needed to better understand the relation between self-reported crime and official arrest records for both gang members and adults.

The fourth limitation to the present study is that the relations in the current study were established through FI cards. Although one prior high profile study used FI card data to build a social network to better understand how social distance is related to shooting victimization (Papachristos et al., 2012), little prior research has examined the extent of missing relational data when using FI cards. This is largely because the sample includes only those who come to the attention of the police. Although a portion of relationships are likely to be missing from these networks, the problem with missing data is mitigated by the fact that gang members experience high levels of police contact, and as a result, a large amount of information is collected on gang members and their associates. Further, gang members hang out on street corners and in groups, making their activities more visible. As this type of research continues, it will be important to better

assess missing relationships in these types of data and to find ways to increase the validity and reliability of FI card data for the purposes of understanding social networks.

Related, the current study relies on one form of relationship between individuals. Some data might be missing from the current study due to the fact that some individuals may have died, gone to jail, or been hospitalized. Combining data sources to determine who should be in the network and identifying other sources of relational data will help to refine the social networks that are built in the future.

There are many other sources of information that could be used to build social networks. For example, arrest reports could be used to establish relationships between co-offenders. Other sources of information, such as co-arrest, victim/witness, court case files, and probation files should be used to build social networks only after research has established the strengths and weaknesses of each source. Specifically, researchers should combine co-arrest data, interviews with patrol officers, probation, parole, and court records for analysis, but it is important to understand the contribution of each data source before combining them for this purpose. Despite these limitations, the current study's findings offer implications for both policy and theory.

Major Findings and Implications

This dissertation presented three research questions and a number of findings associated with each question. Below, the three research questions are discussed along with their theoretical and policy implications. First, chapter 4 presented findings on the nature and utility of relational data taken from field interview cards collected by the police. Second, chapter 5 presented the findings on individual network positions and

criminal behavior measured through arrest. Third, chapter 6 presented the group-level findings on social structure. In the sections that follow, the findings associated with each of the three research questions will be summarized and the implications will be discussed. After the major findings are outlined, the direction for future research is presented.

Research Question 1: Can relational data gathered from the police be used to examine social networks?

The first research question examined whether police data can be used to examine social networks. A number of important findings about gang social networks came from the current study. The social networks that were created for each year from 2006 to 2010 confirmed findings from prior gang literature and also contributed additional findings. Specifically, the social networks had high turnover from year to year, which confirms what is known about the length of time that individuals are in gangs (Thornberry et al., 2003). The networks consisted of small, disconnected groups; this confirms prior research that gang cohesion is found within cliques and not the larger gang (Klein & Maxson, 2006). Finally, the networks revealed insights about hybrid gangs. These findings, which will be discussed further below, suggest that official police data can be used to examine social networks and can help to understand important aspects of gang organization and structure.

Police data, specifically FI card data, can be used to construct social networks and to identify groups and individuals who are central to those groups. As police policymakers begin to understand the utility of such data, efforts can be made to improve the quality of the relational data that are being collected. Below, the specific findings that

came out of this research question will be examined. Additionally, the implications for policy, theory, and methodology will be reviewed.

The first major finding was that the networks that emerged from year to year were not connected networks, but rather were disconnected groups. There was not one large cohesive group; the network consisted of many smaller connected groups. This finding is supported by prior research that suggests that gangs do not typically hang out together, but instead, they socialize in smaller groups of associates (Thrasher, 1927; Decker & Van Winkle, 1996). Specifically, Thrasher found that gang members tended to hang out in “intimacies,” which were small groups of two or three; Decker and Van Winkle found that gang subgroups were typically between two and ten members; and McGloin (2005) found that gangs were organized into small subgroups of individuals.

The difference between being a large connected group and being a number of smaller groups is important. Specifically, in smaller groups it is more likely that information and goods (e.g., drugs, guns) will take longer to disperse throughout the entire network (or to other smaller networks). This finding was replicated across the 5 years of study. That is, the yearly networks looked similar to one another, with a few larger connected groups, some smaller groups, and a series of dyads and isolates. Even though the social network was not a large connected group, the method consistently identified groups, some large and some small, of connected individuals.

The second major finding was that gang members from different cliques were found to be in the same social network. Documented gang members were not only tied to non-gang members (as would be expected), but they were also associated with gang members from other cliques. Although the official police data identified three unique

cliques, the social network visualizations showed that in reality members of different cliques were socially tied to one another. This finding is not necessarily new. Fleisher (2006) found that the networks of three Chicago gangs overlapped. In other words, gang members hang out with members of other gangs (Starbuck, Howell, & Lindquist, 2001).

The third major finding is that high network turnover occurred from year to year. About 80% of those in the sample were present in the network for only one of five years. That is, each year, the social network was comprised of almost entirely new individuals. This high level of turnover is also supported by prior research (Thornberry et al., 2003; Peterson et al., 2004; Esbensen & Huizinga, 1993).

The above findings have important theoretical implications. First, the findings suggest that the line between gang members in one clique, gang members in another clique, and undocumented gang members is not very bright. Gang members in one clique interact with people outside their clique, suggesting that researchers should rethink the unit of analysis. Instead of the gang (or even the clique) being the group unit of analysis, the finding suggests that researchers might better understand gang behavior by examining the social networks of gang members and their associates.

The appropriate unit of analysis might be the social network and not the collection of individuals associated with a particular gang. Because criminal behavior often takes place through social structures (Warr, 2002), our understanding of gang-based social structures might be just as important as our knowledge of the characteristics of the named gang or clique. That is, understanding the informal social structure compared to the formal aspects of the structure (e.g., leadership, rules, signs, symbols) will lead to

insights about the mechanisms that produce crime. We have long known that individuals commit crimes with their friends, and gang members are not any different.

Second, the high rate of turnover in these networks confirmed prior literature that individuals are typically in a gang for a short period of time. Theoretically this finding supports the literature that suggests that gangs are generally unorganized (Decker & Curry, 2000). Similar to how neighborhoods are disorganized because of their high rates of residential mobility (Sampson & Groves, 1989), gangs might lack organizational structure because of their high turnover. That is, high levels of group turnover make structure and organization more difficult to sustain. This finding identifies one of the mechanisms that may prevent gangs from being highly organized. While previous research has found that individuals have short tenures in gangs, the current study examines this from the network perspective. Only about 20% of individuals were in the network more than once over a 5-year period.

The examination of gang social networks in this study found them to be small, loosely organized groups that are comprised of multiple clique members and non-gang members, that have high turnover from year to year. This finding suggests that gangs to do not have high levels of formal organization as some have suggested in the past (Venkatesh, 1997; Taylor, 1990). Further, gangs might not even be as formal as some of the more skeptical academics have suggested (Decker et al., 2008). Researchers have yet to identify the common formal aspects of gang structure that consistently correspond with higher crime and victimization (Pyrooz et al., 2012), studies on the informal social structure of gangs should supplement the theoretical underpinnings of gang organization research.

In addition to the implications to theory, there are a number of policy implications. First, these findings suggest that attention should be focused on groups and the relationships between these groups (McGloin, 2005, 2007). A number of studies have now shown that social process is important for understanding gang behavior and homicides (McGloin, 2007; Papachristos et al., 2012). By network mapping groups of individuals -- specifically those who have been found to be criminally involved -- law enforcement, social service providers, and others can respond more efficiently when crimes occur. For example, imagine a social world where a homicide victim's name, associations, and other important information are readily available immediately after the homicide occurs. Detectives would be able to immediately access social network information and integrate this into their investigation, instead of having to knock on doors to find out who might know something about the individual's social network, wasting valuable time in their response to retaliatory violence.

Further, stakeholders could use the social network information to disrupt the groups that are engaged in violent crime (or any other problem behavior). Instead of focusing on the individuals immediately associated with the crime (suspects), practitioners could focus on the group from which the suspect came (Braga & Weisburd, 2012). If law enforcement and service providers adopt a group approach, they could potentially change the context to which convicted criminals are returned. Prior researchers have frequently discussed the communities and neighborhoods to which offenders return (Clear, 2007), we have rarely discussed the role of the individual's social network in this process. Most offenders will return to the social networks from which they were removed, thus crime reduction strategies should consider the entire network

and the position of the offender as part of re-entry planning. The second policy implication is related to the presence of hybrid gangs (Starbuck et al., 2001). Starbuck et al. reported that gang members can change their affiliation, and gangs can quickly merge with other gangs. The current study offers a new way of documenting the prevalence of hybrid gangs. The current study also found that hybrid groups were more criminally involved than non-hybrid groups. As a result, the findings presented here suggest that it is important for law enforcement to understand the social dynamics of gangs, and this information should be updated as routinely as possible. Tracking the changing affiliations of individuals in hybrid groups would be challenging for law enforcement, but the finding that these groups have an increased likelihood of criminal involvement makes it more urgent that they do so.

The third policy implication is that law enforcement and social service agencies should continue to find ways to disrupt these networks. Ensuring high turnover should help prevent increased gang organization. Further, if law enforcement agencies can build and update social networks, they will be able to identify those individuals who are present in the network from year to year. This is one factor, among others listed later (targeting interventions at those who are most important to the network), that social network analysis can offer to help target suppression and intervention strategies. Those in the network over the long term are providing stability to those networks, and as we have learned from the neighborhood literature, stability can translate into organization (Sampson & Groves, 1989). Organization may be good for a community, but it can also be good for making gangs more efficient criminal enterprises.

In addition to the implications for policy and theory, two other major methodological implications have been drawn from this study. These provide direction for improving the collection and analysis of social network data, using official criminal justice data. First, the networks that emerged limited the types of social network analysis that were possible, and second, police departments should continue to develop records management systems that automatically code relational data.

The groups that emerged in the current study were smaller, disconnected groups that turned over from year to year. The lack of a larger network structure and the high network turnover limited the types of social network analysis that were possible. A number of additional types of analysis are available when there is a complete network with some stability over time. First, blockmodeling could be used to identify network positions and the relations between positions. With a different data structure, this type of analysis would be useful to examine network structure with membership turnover (Lazega, Sapulete, & Mounier, 2009). Specifically, one could identify roles or positions that exist within gangs. The stochastic equivalence blockmodeling process, for example, seeks to identify the number of positions in a network and to partition the individuals in the network according to those positions or blocks. (See Snijders & Nowicki, 2004, for more information on the estimation procedure).

The second type of analysis that should be explored is Simulation Investigation of Empirical Network Analysis (SIENA). The SIENA program is preferable to traditional statistical approaches when conducting social network analysis because it corrects the limitations in previous studies that have examined the relationship between delinquency and social networks. SIENA analyses complete network data, removing the necessity to

collapse network statistics to the individual level. Second, the estimation procedure accounts for the interdependence of individuals within a network (see Steglich, Snijders, & Pearson, 2010). These two types of analysis were not possible in the current study given the high turnover. Future research should examine the networks for shorter time periods, thus increasing stability from one point to the next.

The second methodological implication derived from the current study is that these data are usable for network analysis. FI card data are useful for creating social networks, and these networks will have utility for both academics and law enforcement agencies. Further, both academics and law enforcement agencies should continue to find more efficient ways to collect and manage relational data and to initiate studies to better understand the validity and reliability of such data. For example, when an officer runs a license, or multiple licenses, there should be an indicator that those two individuals were scanned together, thus relating the two. The system should automatically build an edgelist or sociomatrix in the background for later analysis. An agency's ability to disrupt criminal networks is largely limited by its capacity to collect and analyze relational data.

Research Question 2: Are individuals most central to a social network those who are most criminally active and, related, what network positions most accurately identify the most criminally involved individuals?

The second research question asks whether those individuals who were central to the network were the most criminally active and, if so, which type of centrality best predicted criminal behavior. The analysis indicated that betweenness centrality was significantly related to arrest and that this relationship was enhanced by gang membership.

The findings presented in chapter 5 suggested that betweenness centrality was more important within the group than other measures of centrality, with respect to criminal involvement. This finding supports others studies that have suggested that betweenness centrality is a good indicator of those who occupy strategic positions in a network (Morselli, 2010; Papachristos, 2006). Those with high betweenness centrality hold networks together, even though they might not be the most central individuals in terms of the number of connections they hold in the network. Additionally, although three of the four centrality measures did not have an independent effect, there is evidence that centrality contributed to the criminality of gang members. For all four measures of centrality, being more central to the network increased a gang member's likelihood for arrest. In other words, it was not just being a gang member, but it was being a gang member and holding an important network position that increased one's likelihood of arrest. Betweenness centrality, however, increased one's likelihood of arrest more so than the other types of centrality. For non-gang members, only those who were high in betweenness centrality were more likely to be arrested. This interaction between gang membership and betweenness centrality tells us that an individual's position in the network matters.

These findings have a number of implications for theory and the gang organization literature. One's position in the gang has been an important area of inquiry in the gang literature. The current study suggests that researchers should focus on those individuals who bridge groups, that is, those with high betweenness centrality.

Research on gang organization has focused on gang typologies (Klein & Maxson, 2006) and formal indicators of gang organization (Decker et al., 2008). Additionally, a

rich body of qualitative gang literature has revealed the importance of relationships and social networks in how gangs operate. The current study shows that, in fact, understanding the social structure of a gang might be as important as understanding the formal structure. Gangs are not corporate organizations but groups of (typically) young male minorities who hang out and commit crimes together. The informal structure and the social positions within a gang are important for theories of gang formation and evolution, as well as gang prevention, intervention, and suppression efforts.

A recent study by Pyrooz et al. (2012) also highlighted the importance of one's position in a gang. There is some similarity between the approach used by Pyrooz et al. (2012) and the approach used in the current study. Both approaches attempt to identify the variations in gang membership that have both long- and short-term consequences. That is, both seek to show that gang membership is not a homogeneous status and that there is variation in gang membership. More specifically, the two approaches seek to identify a person's level of involvement and commitment to the gang.

The conceptual differences between gang embeddedness, as operationalized by Pyrooz et al. (2012), and a social network approach are rooted in the level of explanation problem that has dogged gang research (Short, 1988). Gang embeddedness is predicated on an individual's self-reported perception of the gang, with respect to both their position in it and its meaning to them. From this perspective, gang embeddedness can be determined from the individual. This is not true of the social network perspective. The current study presents the social structure of the gang. The social structure can neither be reconstructed from the perspective of a sample of individuals nor from the perspective of only the gang members. Instead, one's network position is based on observed behavior

instead of self-reported behavior. One's position in the network is based on one's relations and position relative to everyone else in the group.

Further, there are some important consequences from using one or the other of the two theoretical approaches. First, it is unlikely that most of the individuals in a group are even aware of their network positions. The gang could in fact be very important to a gang member; he or she could hang out with the gang frequently, commit crimes with the gang, and consider himself (or herself) a leader, but that same individual might not occupy an important or strategic network position. That embedded individual may or may not be important to the diffusion of information throughout the network. Second, individuals with high betweenness centrality probably spend time with different groups of people, both gang and non-gang, and so might not be considered to have high gang embeddedness. Stated differently, someone who is highly embedded in a group would more likely have higher degree or eigenvector centrality, as opposed to betweenness centrality. Whereas gang embeddedness identifies those who are committed, dedicated, and integrated into the gang lifestyle, network position identifies those who are strategically placed within the social structure of gang members and gang associates.

The consequences of the theoretical approaches and their relation to various behavioral outcomes are still to be discovered. It has been shown that gang embeddedness impacts the duration of gang membership (Pyrooz et al., 2012); it is still unclear, however, how knowledge of gang embeddedness can inform intervention and suppression strategies. The policy implications for network position have been outlined here, but the long-term implications for behavioral outcomes that are related to network position are not yet fully understood.

Network position is valuable for gang response strategies in that individuals typically are not aware of their own network position. Just as we are often unaware of our role in the spread of a virus (i.e., did we have high degree centrality or betweenness centrality in the recent spread of the common cold?), gang members are likely to be unconscious of their precise role in the spread of information and/or culture. In this way, reconstructing social networks offers law enforcement and social service agencies the upper hand in understanding gang social structure and the processes of the group. There are still many questions to be answered, however, before we have untangled the relations between gang embeddedness, network position, formal organizational structure, and social structure.

Also in terms of theory, the finding that network position is related to behavior contributes to our understanding of the function of groups. Social learning theory describes the mechanisms for influence in social networks. The current study found that both gang affiliation and network position matter. Does one's position in the network dictate the ability to influence or be influenced by others in the network? The current study suggests that position in the network is important, but future studies should further examine how criminal behavior is spread throughout a network. Specifically, what roles do gang membership and network position play in the spread of crime? Some positions likely make individuals more vulnerable than others. In the same way that the spread of disease travels from person to person, the spread of crime and violence moves through social networks (Papachristos et al., 2012). The current study makes evident that gang members who occupy key network positions likely play an important role in this process. Further, being in a gang facilitates a person's own criminal behavior (Thornberry et al.,

1993). To extend this line of research, the current study found that not only is it important to be in a gang, but your position in the network is also related to behavior. Theorists should continue to develop social learning theory, focusing on the role susceptibility and influences of specific network positions.

For policy purposes, the findings related to network position clearly support the design of network-based interventions and suggest that knowledge about network position can help law enforcement and social service agencies target interventions and services toward specific individuals. Gang members or associates at the periphery of the network might be better candidates for social service intervention compared to one who is more central to the network (McGloin, 2005). By removing those with high betweenness centrality from the network, one will disrupt the flow of information in the network.

One advantage of the current study is that it uses existing law enforcement data to construct the social organization of groups. Other than perhaps needing training in social network analysis techniques, law enforcement agencies already have the data and infrastructure needed to identify those individuals with high betweenness centrality in criminal networks operating in their jurisdictions.

A second policy implication can be drawn from the finding that network position is important. A number of strategies have been implemented that incorporate the use of social network analysis to identify individuals for arrest and prosecution (McGloin, 2005; Morselli, 2009). The current study supports the use of social network analysis to target offenders using a focused-deterrence approach (Braga & Weisburd, 2012). Social network analysis has been used in focused-deterrence strategies around the country

(Engel et al., 2011; Braga & Weisburd, 2012). The evidence suggests that identifying violent groups and holding them accountable for the actions of the group holds promise for reducing violent crime (Braga & Weisburd). The use of social network analysis in these strategies is not new; however, the use of social network analysis should be expanded. As practitioners continue to identify the important players in criminal networks for arrest and prosecution, this same information can be used to match individuals with social services. Violent individuals with high betweenness centrality might be good candidates for arrest and prosecution. Additionally, individuals on the periphery of the network, and even those with high degree centrality who do not have a history of violence might be good candidates for targeted social services. These individuals should be targeted by social service agencies to provide education, job training, health care, or whatever other needs the individual might have. Helping to move an individual out of a crime-prone social network will further prevent the spread of violence and delinquency.

In the same way that we do not wait on individuals to turn themselves in when they have been identified for arrest, practitioners should not provide social services only when a candidate walks through the door. To impact these networks, interventions (both arrest and social services) must be proactively employed. The incorporation of social network analysis into focused deterrence strategies and other law enforcement responses are essential to ensure that the limited resources are used in the most efficient way possible.

Research Question 3: What are the network structures that differentiate gangs, and are these structures related to group-level crime?

The third and final research objective was to better understand the variation in group social structure and how that is related to group-level criminal behavior. The answer to this question is that gang cliques do not have separate structures. Instead, they overlap with each other. Additionally, while we found high levels of cohesion among components, none of the group-level structures were discovered to be related to arrests at the group level. The previous section showed that position in the network was related to criminal behavior; at the group level, however, there was no evidence that social structure was related to group-level offending.

We found significantly more cohesion among gang networks than would have occurred if the networks had been randomly generated. This approach can be used in future research to assess whether gang networks are more or less cohesive than other criminal and non-criminal groups. In terms of the gang organization literature, many different conceptualizations of gang organization have been largely determined by the method of data collection. The ethnographic gang literature has historically noted the importance of social networks and relationships for the function of the gang, but the empirical analysis of social networks has not always been available.

The social network approach provides an alternative methodology for understanding gang organization that complements both the individual-level indicators approach (Decker et al., 2008; Pyrooz et al., 2012) and the typology approach (Klein & Maxson, 2006). It is difficult to reconcile these at this point, but the possibilities for future research comparing the different approaches are endless. Are the network

structures different between typologies? Do leaders occupy an identifiable position in the network? The presented methodological approach offers a systematic data collection procedure that can be used to understand these issues across many gangs. This would help eliminate sample selection bias that comes along with some qualitative gang research. Some researchers have been criticized for selecting the most organized gangs for examination. The methodological approaches in the current study could be applied to any group, and the results compared.

A second major finding related to group-level social structure from this study is that a relation between group level network measures and arrest could not be established. Despite sufficient power to detect a large effect (power = 0.984), and reasonable power to detect a medium effect (power = 0.747), the relation could not be established. The possibility remains, however, that there might be a small, but significant relation between group-level social structure and group-level criminality.

In terms of theory, more is yet to be discovered about the role of social cohesion and gangs. First, studies have pointed out that gangs vary in their level of cohesion (Klein, 1971; McGloin, 2005); we still need to know more about the consequences of cohesion. As we establish the relationship between cohesion and criminal behavior, it then becomes important to identify the mechanisms that lead to increases in cohesion. The current study measures social cohesion through group-level density measures. Although density was not a predictor of group-level rates of arrest, there may be other consequences of increased social cohesion. Other measures of criminal behavior should be studied in relation to social cohesion. Importantly, future research should examine whether the social cohesion of the group impacts the length of gang membership or the

long-term consequences of gang membership (Pyrooz, 2012). Haynie (2001) found that one's ego network was related to delinquency. The current study did not find that group-level density measures were related to the group rate of arrest. Thus, the individual-level finding did not translate into the group level in the current study. The group level structure matters when identifying the positions that individuals occupy. Based on the current study, group-level structure is not associated with group-level criminality. Cohesion and the collective identity are likely to have impacts on other aspects of gang life, a point that will have to be examined in future research.

Additionally, the current study found that the average age of the group members was related to the rate of arrest. Theoretically, this finding is important in light of Morselli's (2009) prior work that found that younger individuals were associated with higher degree centrality and older individuals tended to have higher betweenness centrality. As more information about the evolution of groups emerges, researchers should identify the mechanisms through which individuals move into high betweenness centrality positions.

The policy implications of using network analysis to study gangs have been outlined before by McGloin (2005) and others (Morselli, 2009; Rostami & Leinfelt, 2011). Information about the level of cohesion of a gang and the positions within the gang will be strategically valuable for both law enforcement and social services. For instance, the collective accountability approach might be more effective for combatting a cohesive gang, but would be less effective for a loose knit, disconnected network (McGloin, 2005). Further, the current study suggests that law enforcement should focus on strategically placed individuals instead of entire groups. It is important to note that

analysts can only identify the important individuals by first understanding the group social structure. Practitioners should first identify the important groups, followed by the identification of individuals within those groups.

Second, the finding that member age is related to a higher proportion of group members being arrested suggests that researchers should pay more attention to adult gang members. Findings in the gang literature have largely been drawn from youth populations and school-based samples (Esbensen & Huizinga, 1993; Esbensen & Winfree, 1998; Gordon et al., 2004). This finding about age is not conclusive, but it does suggest that researchers should expand their quantitative studies to include adults. A good example would be to implement a gang addendum into the Arrestee Drug Abuse Monitoring Program that is funded by the Office of National Drug Control Policy.

Future Research

The current study has identified a number of areas for future study. First, future research should determine how conservative FI cards are as a measure of social relationships. Second, researchers should identify the long-term outcomes of network position. Mirroring the work done by Pyrooz (2012), researchers should identify those who have the most negative long-term outcomes. Third, the current approach opens new doors for gang research. Specifically, researchers should use similar data to expand their understanding of hybrid gangs. Last, network data provide a unique opportunity to engage in multi-level analysis of individuals nested within gangs.

The first area for further study has to do with the measure of relations. The current study uses FI cards. These are a conservative measure of relatedness and have been used

recently to better understand the role of social networks in violent victimizations (Papachristos, Braga, & Hureau, 2012). Future research should examine just how conservative this measure of relatedness is. There are a couple of ways one could examine this further. First, these networks can be taken to patrol officers to examine whether the constructed networks have face validity. Patrol officers could speak to the extent to which relationships might be missing. The second strategy that should be pursued is to make contact with individuals who occupy strategic network positions. Interviews could be conducted with these individuals to verify whether they actually occupy the position in the network suggested by the analysis. These two approaches would greatly contribute to understanding the quality of FI card data for the purposes of constructing social networks.

Second, future research should examine the consequences of network position. This could be examined through the use of network data collected by Walter Miller in the 1950s, for example. Miller collected thousands of contact cards allowing for researchers to reconstruct the networks that existed at the time. After identifying the network positions of each person, researchers could establish the relation between network position and life outcomes. How did the life outcomes of those with high betweenness centrality differ from those high in degree centrality? If researchers knew more about the long-term effects of the network, they could do more to intervene as the network forms. If it is the case that those with high levels of one type of centrality are found to have more negative life outcomes, early interventions can be targeted at those individuals.

The third area of future research is to unpack the scope and nature of hybrid gangs and how they might differ from other gangs. At least a few studies already suggest that

the networks of different gangs frequently overlap (Fleisher, 2006; Morselli, 2009).

Associated with this finding, researchers should determine how hybrid groups differ from those that are more homogeneous. Do hybrid groups present more criminal opportunity? Are different gang members coming together for business or for friendship? There is still a lot to learn about these groups.

Finally, future studies should examine gangs at the individual and group levels. Collecting data at both levels will allow researchers to develop multi-level theories about gang involvement. Specifically, future research should examine how group-level structure impacts individual-level behavior. The systematic collection of gang social network data will continue to open doors for further research about gang organization, social structure, and social process.

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APPENDIX A
TERMINOLOGY

The following definitions were provided by Wasserman and Faust (1994) and de Nooy et al. (2011) and come directly from the above text.

Betweenness Centrality: Using the concept of the geodesic (the shortest distance between two individuals), betweenness centrality is calculated as the proportion of all geodesics that include the particular node. That is, the proportion of shortest distance communication chains included in a given node, the more geodesics a node is included in, the more information they potentially control and the more important they are to the network.

Betweenness Centralization: Betweenness centralization measure is calculated as the variation in betweenness centrality measures (the individual-level measure of betweenness) divided by the maximum possible variation in betweenness centrality in a network of the same size. Again, higher variation is an indication the network is more centralized, that information must flow in distinct ways and not through random avenues.

Centrality: A centrality measure is a score that is given to each individual and is an indication of the individual's importance to the network based on different operationalizations of centrality.

Centralization: Centralization measures the flow of information throughout the network. High levels of network centralization indicate role differentiation in the network.

Closeness Centrality: Closeness centrality is calculated as the number of other nodes in the network divided by the sum of the geodesic distances between that node and all other nodes in the network. As a result, if a node was directly connected to all other nodes in the network, their closeness centrality score would be one; as the distances become greater, their score becomes something less than one.

Closeness Centralization: Closeness centralization measures social distance through geodesics. A geodesic is the shortest path between two nodes in a network and the length of a geodesic is referred to as the distance between the two nodes. Closeness centralization is calculated as the variation in the average distances (using the geodesics) of nodes divided by the maximum possible variation in closeness scores.

Degree Centrality: The degree centrality of a node is simply the degree of that particular node. Once again, the degree of a node is equal to the number of ties a node has in the network.

Degree Centralization: Degree centralization is a measure ranging from 0 to 1, with 1 indicating the most centralized network. The degree of a node is the number of ties it has to other nodes in the network. Thus, the degree centralization is calculated as the variation in degree among nodes divided by the maximum possible variation in a network of the same size.

Degree: (*indegree, outdegree*): The degree of a node is equal to the number of ties connected to it. This is a number that ranges from 0 to the total number of actors in the sociogram. If the ties are directed (person A indicates a relationship with person B, but B does not indicate a relationship with A), then the indegree of that node will be the number of relationships a person receives (the number of times he or she was chosen by another person), and the outdegree is the number of relationships sent out.

Density: A density measure is the proportion of ties that exist over the total number of ties that could potentially exist.

Eigenvector Centrality: Eigenvector centrality denotes that a person is central to a network to the extent that they are centrally located, but also to the extent that they are connected to others who are centrally located. Thus, the centrality of one's friends is taken into account by including not just who you know, but by who your friends know as well.

Eigenvector Centralization: Eigenvector centralization adds the weight of who your associates know. It is not just who you know, but how connected your friends are to others in the network. Eigenvector centralization is calculated as the variation in eigenvector centrality (individual measure of eigenvector centralization) divided by the maximum possible variation in eigenvector centrality.

Node: In a graph, nodes represent the actors or people and are generally represented by a circle. In graph theory, the nodes are also referred to as vertices or points.

Sociogram: A picture in which people (or some other social unit) are represented as points in two-dimensional space. The relationships between two people are represented by a line or an arrow. Sociograms are also referred to as graphs or network maps.

Tie: The link between two nodes in a sociogram is referred to as a tie. These lines are also referred to as edges, if they are non-directional and as arcs if they are directed.

APPENDIX B

THE STRUCTURE OF A TRADITIONAL GANG



Source: Klein, 1995